Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources

Final Report and Peer Review Report

EPA United States Environmental Protection Agency

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Final Report and Peer Review Report

Assessment and Standards Division
Office of Transportation and Air Quality
U.S. Environmental Protection Agency

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Executive Summary

Since the late 1990s, EPA's Office of Transportation and Air Quality (OTAQ) has included a learning effect in our estimates of the costs of regulatory packages. In its most basic formulation, the learning curve reflects the simple idea that the more a person does something, the better the person can do it. This idea can also be applied to organizations: "as organizations gain operating experience, organizational performance improves, albeit at a decreasing rate" (Lapre and Nembhard 2010, p. 3). When applied to OTAQ's economic analyses, this means that the cost of applying emission control technology decreases as the production volume of compliant engines and equipment increases.

The application of the learning effect to organizations has been studied by academia and industry for more than 60 years, and is well-known and well-accepted. In addition, there is more and more research that seeks to quantify the learning effect for individual industries. This research ranges from analysis of specific companies based on confidential plant-level data to broad, industry sector studies based on national economic census data.

A brief summary of the way OTAQ has incorporated learning into our cost analyses is set out below. To improve and validate our cost analysis methodology, OTAQ engaged ICF, assisted by a Subject Matter Expert, Dr. Linda Argote of Carnegie Mellon University, to examine recent empirical research on the learning effect (defined as the relationship between the volume of production and unit costs) for manufacturing generally and the mobile source industry in particular.[1] The study has three goals:

- Provide a definitive, up-to-date, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically;
- Gather into a single compendium study recent empirical research on industrial learning in the mobile source sector for use in future OTAQ costs analyses; and
- Using the information drawn from the empirical studies, provide an estimated summary effect of learning in mobile source industries.

The ICF study, "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources," is contained in Part I of this report. Section 2 of the ICF study describes how ICF and the Subject Matter Expert identified the 55 published articles that form the reference list for the study. All of these articles confirm the existence of the learning effect, and none of them suggest that learning does not occur in organizations. Twenty-nine of the articles address learning effects in the manufacturing sector generally; 8 of these were selected

[1] OTAQ originally requested ICF to provide estimates of the learning effect separately for each of the specific mobile source sectors (e.g., original equipment auto makers, parts suppliers to those auto makers, loose engine manufacturers, large truck manufacturers, and nonroad equipment manufacturers) for which studies are found that address those specific sectors. However, the literature did not support the development of unique estimates and therefore only one progress ratio for the mobile source sector was estimated.

for in-depth review. Twenty-six of the articles address learning effects in the mobile source sector specifically; 10 were selected for in-depth review and the other 16 received a cursory review. The appendix to this Executive Summary lists the 55 articles that form the basis of the ICF study.

Section 3 of the ICF study describes the economic theory behind learning curves and progress ratios and provides a summary table of the key findings of the articles selected for in-depth review[2]; the articles are reviewed in Section 4. Most importantly, Section 3 also provides an estimated mobile source progress ratio on the basis the results reported in 5 of the mobile source articles (see Table 2 of the ICF study), using a weighted mean approach. The recommended mobile source progress ratio is 84.3 percent, with a 95 percent confidence interval of 83.9 percent to 84.8 percent.

The ICF study was peer reviewed pursuant to EPA's *Science Policy Council Peer Review Handbook*, 3rd edition (*Peer Review Handbook*).[3] In their general comments, the peer reviewers were very supportive of the study:

- I find the report to be comprehensive, and I believe it does a good job of characterizing the rates of learning typically found in transportation equipment manufacturing plants. … [T]he EPA report offers a more in-depth view of the literature on industrial learning that is most relevant to the mobile source sector. Overall, I find the report to be a well-executed document that is likely to be helpful in providing a basis for incorporating forecasts of learning into EPA and other government rulemaking. (Lieberman)
- On balance, the study is a very fine review of the literature on learning by doing in general, but especially with regard to its manifestation in manufacturing operations during the past few decades. The report is notably comprehensive within this scope, makes sensible topical categorizations in its discussion of the literature's findings, and is clearly written. … In sum, it is my opinion that the report does achieve the intended goal of being a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically. (Syverson)
- The overall presentation and organization of the Report is generally clear. However, there are some specific areas that require greater clarity. These are described below. (Balasubramanian)

[2] There are 21 articles included in this table: 18 articles selected for in-depth review as well as three others that were deemed important.

[3] These guidelines can be found at http://www.epa.gov/peerreview/. Further, the Office of Management and Budget's (OMB's) Information Quality Bulletin for Peer Review and Preamble (found in the EPA's *Peer Review Handbook*, Appendix B) contains provisions for conducting peer reviews across federal agencies and may serve as an overview of EPA's peer review process and principles. The results of the peer review of this study are included in the Appendix to this report.

Part II of this report contains information about the peer review, which was performed for OTAQ by RTI International, and all of the peer review comments. The ICF responses to the peer review comments are set out in Section 5 of the ICF study. It should be noted that while the peer reviewers commented on the methodology used to estimate the recommended mobile source progress ratio, those comments did not lead the Subject Matter Expert to change that methodology or revise that estimate.

Learning Effect in OTAQ's Cost Analyses

EPA's Office of Transportation and Air Quality (OTAQ) has included learning effects in its cost estimates for its rulemaking packages beginning with its 1997 rule adopting emission standards for Model Year 2004 heavy-duty engines (62 FR 54694, October 21, 1997).[4] Table 1 provides information on many of these rules and how they incorporated learning.

As explained in the 1997 heavy-duty rule, "[r]esearch in the costs of manufacturing has consistently shown that as manufacturers gain experience in production, they are able to apply innovations to simplify machining and assembly operations, use lower cost materials, and reduce the number or complexity of component parts" (62 FR 54711, October 21, 1997). To incorporate this principle, OTAQ used a learning curve algorithm that applied a learning factor of 20 percent (80 percent progress ratio) for each doubling of cumulative production volume. This approach was simplified by using a time-based learning progression rather than a pure production volume progression (i.e., after a specified number of years of production it was assumed that cumulative production volumes would have doubled and, therefore, costs would be reduced by 20 percent). This approach of reducing costs in discrete steps, with a varying number of steps depending on the novelty of the relevant technology, was used through the 2008 Small SI rule (also called the Bond Rule, 73 FR 59034, October 8, 2008).

Beginning with the first light-duty greenhouse gas rule (EPA420-R-10-109, April 2010), OTAQ began to apply a more nuanced approach to incorporate learning effects in cost analyses, in which the rate of learning and therefore the level of cost reduction due to learning depends on where on the learning curve a technology's learning progression is. In this approach, the steep-portion learning algorithm applies to those technologies considered to be newer technologies likely to experience rapid cost reductions through manufacturer learning and the flat-portion learning algorithm applies to those technologies considered to be mature technologies likely to experience minor cost reductions through manufacturer learning.[5] Costs for newer technologies,

[4] In 1977, a contractor commissioned by EPA developed "estimates of the retail price equivalent or "sticker price" for a variety of automotive exhaust emission control related components/systems," which included a learning component. Learning was estimated based on prices from U.S. and European sources for varying quantities of specific components. Based on those prices, a progress ratio of 91.4 percent was estimated. EPA 1980, Cost Estimates for Emission Control Related Components/Systems and Cost Methodology Description, Heavy Duty Trucks, EPA-460-3-80-001, February 1980; see also EPA 460/3-78-002 (report date December 1977).

[5] Initially, OTAQ distinguished between "volume-based" learning (steep portion of the learning curve) and "time-based" learning (flat portion of the learning curve); see EPA 420-4-10-901, April 2010, p. 3-18. However, as noted in the Heavy-Duty GHG rule, OTAQ quickly recognized that

said to be on the "steep" portion of the learning curve, were reduced by 20 percent at discrete intervals; later, and for mature technologies said to be on the "flat" portion of the learning curve, costs were reduced at a decreasing percentage (three, then two, then one percent) and at longer intervals.

In its 2014 report, the National Research Council of the National Academy of Sciences noted that "[a]lthough technological change is certain, its direction, magnitude, and impacts on cost are difficult to predict. For most components, manufacturing costs tend to decrease with increased production volumes and with the accumulation of experience. However, there are no exact methods for predicting future rates of learning by doing or technological progress" (NAS 2014, p 245, 250). The authors note that EPA uses an unconventional approach for learning, as a function of time rather than volume. Their recommendation 7.2 states:

> The Agencies should make clear the terminology associated with learning and should assess whether and how volume-based learning might be better incorporated into their cost estimates, especially for low volume technologies. The Agencies should also continue to conduct and review empirical evidence for the cost reductions that occur in the automobile industry with volume, especially for large-volume technologies that will be relied on to meet the CAFE/GHG standards. NAS 2014, p. 259-60.

To ensure that the learning effects incorporated in OTAQ's cost estimates are based on a comprehensive survey of the literature, OTAQ engaged ICF, with the assistance of a Subject Matter Expert (Dr. Linda Argote of Carnegie Mellon University), to develop a single compendium study on industrial learning in the mobile source sector. This report contains the results of that study.

> …all learning is, in fact, volume-based learning, the level of cost reductions depend only on where on the learning curve a technology's learning progression is. We distinguish the flat portion of the curve from the steep portion of the curve to indicate the level of learning taking place in the years following implementation of the technology." (EPA 420-R-11-901, August 2011, p. 2-9)

More recently, in the Light-Duty GHG rule, EPA explained

> … we have updated our terminology in an effort to clarify that we consider there to be one learning effect—learning by doing—which results in cost reductions occurring with every doubling of production. In the past, we have referred to volume-based and time-based learning. Our terms were meant only to denote where on the volume learning curve a certain technology was—"volume-based learning" meant the steep portion of the curve where learning effects are greatest, while "time-based learning" meant the flatter portion of the curve where learning effects are less pronounced. Unfortunately, our terminology led some to believe that we were implementing two completely different types of learning—one based on volume of production and the other based on time in production. Our new terminology—steep portion of the curve and flat portion of curve—is simply meant to make more clear that there is one learning curve and some technologies can be considered to be on the steep portion while others are well into the flatter portion of the curve. (EPA 420-R-12-901, August 2012, p. 3-23)

Table 1 - OTAQ Rules Incorporating Learning Effects in Cost Analyses, 1997-2008

Rule	Federal Register Citation	Technologies	Learning Progress Ratio	New or Mature Technology
1997 Heavy-duty MY2004 Highway Rule	62 FR 54694 (10/21/97)	Fuel system changes; EGR	- One 20% learning curve reduction - Applied in Year 3	Rule met via changes to existing technology RIA EPA420-R-97-011, September 1997
1998 Nonroad Diesel Tier 2 & 3	63 FR 56968 (10/23/98)	Fuel system changes; EGR	- Two 20% learning curve reductions - Applied in Years 3 and 6	Rule met via application of emission controls to the sector for the first time RIA EPA420-R-98-016; August 1998
1999 Marine Diesel Rule	64 FR 73300 (12/29/99)	Fuel system changes; EGR	- Two 20% learning curve reductions - Applied in Years 3 and 6	Rule met via application of emission controls to the sector for the first time RIA EPA420-R-99-026; November 1999
2000 Tier 2 Light-duty Highway Rule	65 FR 6698 (2/10/00)	catalyst; secondary air injection, fuel control, exhaust system changes, combustion chamber changes, EGR	- One 20% learning curve reduction - Applied in Year 3	Rule met via changes to existing technology RIA EPA420-R-99-023; December 1999
2000 Tech Review of HD2004 Rule	65 FR 59896 (10/6/00)	Fuel system changes; EGR	- One 20% learning curve reduction - Applied in Year 3	Rule met via changes to existing technology RIA: EPA420-R-00-010; July 2000
2001 Heavy-duty MY2007 Highway Rule	66 FR 5002 (1/18/01)	Aftertreatment systems including in-exhaust reductant injectors, catalyst components	- Two 20% learning curve reductions - Applied in Years 3 and 5	Rule met via new technology RIA: EPA420-R-00-026; December 2000
2002 Nonroad Large SI and Recreational Engines Final Rule	67 FR 68242 (11/8/02)	Recalibration, fuel system upgrades; improved combustion and aftercooling	- Two 20% learning curve reductions - Applied in Years 3 and 6	Rule met via application of emission controls to the sector for the first time RIA: EPA420-R-02-022; September 2002

Rule	Federal Register Citation	Technologies	Learning Progress Ratio	New or Mature Technology
2004 Nonroad Tier 4 Rule	69 FR 38958 (6/29/04)	Aftertreatment systems including in-exhaust reductant injectors, catalyst components; EGR	- One 20% learning curve reduction - Applied in Year 3 - Starting point was the Year 3 HD2007 Rule	Rule met via HD2007 technology applied to nonroad engines for first time RIA: EPA420-R-04-007; May 2004
2008 LocoMarine Rule	73 FR 37096 (6/30/08)	Aftertreatment systems including in-exhaust reductant injectors, catalyst components	- One 20% learning curve reduction - Applied in Year 3 - Starting point was the Year 3 NRT4 Rule	Rule met via HD2007/NRT4 technology applied to LocoMarine engines for first time RIA: EPA420-R-08-001; May 2008
2008 Nonroad Small SI Rule (Bond Rule)	73 FR 59034 (10/8/08)	Catalyst, combustion chamber changes, improved fuel systems	- One 20% learning curve reduction - Applied in Year 6	Rule met via changes to existing technology RIA: EPA420-R08-014; September 2008
2010 Light-duty GHG Rule	75 FR 25324 (5/7/10)	Fuel consumption reducing powertrain and vehicle technologies along with vehicle electrification technologies	Technology dependent – technologies were placed on the steep or flat portion of the typical learning progression; as in above analyses, time was used as a proxy for production volumes	Joint TSD: EPA420-R-10-901; April 2010
2011 Heavy-duty GHG rule	76 FR 57106 (9/15/11)	Fuel consumption reducing powertrain and vehicle technologies along with vehicle electrification technologies	Technology dependent – technologies were placed on the steep or flat portion of the typical learning progression; as in above analyses, time was used as a proxy for production volumes	RIA: EPA420-R-11-901; August 2011

Rule	Federal Register Citation	Technologies	Learning Progress Ratio	New or Mature Technology
2012 Light-duty GHG rule	77 FR 62624 (10/15/12)	Fuel consumption reducing powertrain and vehicle technologies along with vehicle electrification technologies	Technology dependent – technologies were placed on the steep or flat portion of the typical learning progression; as in above analyses, time was used as a proxy for production volumes	RIA: EPA420-R-12-016; August, 2012; Joint TSD: EPA420-R-12-901; August 2012
2014 Tier 3 Light-duty Highway Rule	79 FR 23414 (4/28/2014)	catalyst; secondary air injection, fuel control, exhaust system changes, combustion chamber changes, EGR	Technology dependent – technologies were placed on the steep or flat portion of the typical learning progression; as in above analyses, time was used as a proxy for production volumes	RIA: EPA420-R-14-005; February 2014
2015 Heavy-duty GHG proposed rule	80 FR 40138 (7/13/2015)	Fuel consumption reducing powertrain and vehicle technologies along with vehicle electrification technologies	Technology dependent – technologies were placed on the steep or flat portion of the typical learning progression; as in above analyses, time was used as a proxy for production volumes	RIA: EPA420-D-15-002; June 2015

Appendix: List of 55 Articles that Form the Basis of the ICF Study

1. Learning in Manufacturing in General – Articles selected for detailed review (8 articles)

Argote, Linda, Dennis Epple. 1990. Learning curves in manufacturing. Science, 247(4945), 920-924. http://www.sciencemag.org/content/247/4945/920.short

Argote, Linda. 2013. Organizational learning: Creating, retaining and transferring knowledge. Springer.(Chapters 1. 3 and 6) https://faculty.fuqua.duke.edu/~charlesw/s591/willstuff/oldstuff/PhD_2008_2009_LongStrat/Readings/Class07_Learning/Organ001.pdf

Bahk, B., & Gort, M. 1993. Decomposing learning by doing in new plants. Journal of Political Economy, 101, 561-582. http://www.jstor.org/discover/10.2307/2138739?uid=3739936&uid=2&uid=4&uid=3739256&sid=21103414588873.

Balasubramanian, Natarajan, and Marvin B. Lieberman. 2010. Industry learning environments and the heterogeneity of firm performance. Strategic Management Journal 31.4, 390-412. http://www.anderson.ucla.edu/faculty/marvin.lieberman/docs/Balasubramanian-Lieberman-SMJ-April2010.pdf

Dutton, John, Annie Thomas. 1984. Treating Progress Functions as a Managerial Opportunity. The Academy of Management Review, 9(2), 235-247. http://www.jstor.org/discover/10.2307/258437?uid=3739936&uid=2&uid=4&uid=3739256&sid=21103550037613

Lapre, Michael A, Ingrid M Nembhard. 2010. Inside the Organizational Learning Curve: Understanding the Organizational Learning Process. Foundations and Trends in Technology, Information and Operations Management, 4(1), 1-103. http://resource.owen.vanderbilt.edu/facultyadmin/data/research/2265full.pdf.

Macher, J.T., & Mowery, D. C. 2003. Managing learning by doing: An empirical study in semi-conductor manufacturing. Journal of Product Innovation Management, 20(5), 391-410. http://faculty.msb.edu/jtm4/Papers/jpim.2003.pdf

Rubin, Edward S., et al. 2004. Learning curves for environmental technology and their importance for climate policy analysis. Energy 29, 1551-1559. http://energy.lbl.gov/staff/taylor/pdfs/rubin-taylor-energy-2004.pdf

2. Learning in Manufacturing in General – Articles not selected for review (21 articles)

Adler, P. S., & Clark, K. B. 1990. Behind the learning curve: A sketch of the learning process. Management Science, 37, 267-281. http://www-bcf.usc.edu/~padler/research/Behind%20the%20Learning%20Curve-1.pdf

Balasubramanian, Natarajan, and Marvin B. Lieberman. 2011. Learning-by-doing and market structure. The Journal of Industrial Economics 59.2, 177-198. http://164.67.163.139/Documents/areas/fac/policy/learning_marketstructure.pdf

Day, George S., and David B. Montgomery. 1983. Diagnosing the experience curve. The Journal of Marketing, 44-58. https://gsbapps.stanford.edu/researchpapers/library/RP641.pdf

Ghemawat, P. 1984. Building strategy on the experience curve. Harvard Business Review, 63, 143-149. http://hbr.org/product/building-strategy-on-the-experience-curve/an/85206-PDF-ENG

Heim, J. 1992. Manufacturing systems: foundations of world-class practice. Committee on Foundations of Manufacturing, National Academy of Engineering. http://www.nap.edu/catalog.php?record_id=1867

Hendel, I. and Spiegel, Y. 2014. Small steps for workers, a giant leap for productivity. American Economic Journal: Applied Economics. 6.1, 73-90. January 2014. https://www.aeaweb.org/articles?id=10.1257/app.6.1.73

Irwin, Douglas, Peter Klenow. 1994. Learning-by-Doing Spillovers in the Semiconductor Industry. The Journal of Political Economy, 102(6), 1200-1227. http://www.jstor.org/discover/10.2307/2138784?uid=3739936&uid=2&uid=4&uid=3739256&sid=21103414588873

Jarmin, R.S. 1994. Learning by doing and competition in the early rayon industry. The Rand Journal of Economics, 25, 441-454. http://www.jstor.org/discover/10.2307/2555771?uid=3739936&uid=2&uid=4&uid=3739256&sid=21103550037613

Klenow, Peter J. 1998. Learning curves and the cyclical behavior of manufacturing industries. Review of Economic Dynamics 1.2, 531-550. http://www.klenow.com/REDLC.pdf

Laitner, John A"Skip, and Alan H. Sanstad. 2004. Learning-by-doing on both the demand and the supply sides: implications for electric utility investments in a Heuristic model. International Journal of Energy Technology and Policy 2.1, 142-152. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.202.8902&rep=rep1&type=pdf

Lapre, Michael A, Amit Shankar Mukherjee, Luk Van Wassenhove. 2000. Behind the Learning Curve: Linking Learning Activities to Waste Reduction. Management Science, 46(5), 597-611. http://www.jstor.org/discover/10.2307/2661461?uid=3739936&uid=2&uid=4&uid=3739256&sid=21103550037613

Lieberman, Marvin B. 1984. The learning curve and pricing in the chemical processing industries. The RAND Journal of Economics 15.2, 213-228. http://www.anderson.ucla.edu/faculty/marvin.lieberman/publications/LC-Rand1984.pdf

Lieberman, Marvin B. 1987. Market growth, economies of scale, and plant size in the chemical processing industries. The Journal of Industrial Economics, 175-191. http://www.anderson.ucla.edu/faculty/marvin.lieberman/publications/PlantSize-JIE1987.pdf

Lieberman, Marvin B. 1987. Patents, learning by doing, and market structure in the chemical processing industries. International Journal of Industrial Organization 5.3, 257-276. http://www.sciencedirect.com/science/article/pii/S0167718787800097

Lieberman, Marvin B. 1987. The learning curve, diffusion, and competitive strategy. Strategic management journal 8.5, 441-452. http://www.anderson.ucla.edu/faculty/marvin.lieberman/publications/LC-Strategy-SMJ1987.pdf

Lieberman, Marvin B. 1989. The learning curve, technology barriers to entry, and competitive survival in the chemical processing industries. Strategic Management Journal 10.5, 431-447. http://www.anderson.ucla.edu/faculty/marvin.lieberman/publications/LC-Survival-SMJ1989.pdf

Nagy, Béla, et al. 2013. Statistical basis for predicting technological progress. PloS one 8.2, e52669. http://www.plosone.org/article/info%3Adoi%2F10.1371%2Fjournal.pone.0052669

Sinclair, G., Klepper, S., & Cohen, W. 2000. What's experience got to do with it? Sources of cost reduction in a large specialty chemicals producer. Management Science, 46, 28-45. http://pubsonline.informs.org/doi/abs/10.1287/mnsc.46.1.28.15133

Suarez, Fernando, Michael Cusumano, Charles Fine. 1996. An Empirical Study of Manufacturing Flexibility in Printed Circuit Board Assembly. Operations Research, 44(1), 223-240. http://people.bu.edu/suarezf/Fernando_Suarez_Website/Publications_files/1996_An%20Empirical%20Study%20of%20Manuf%20Flexibility_Suarez_Cusumano_Fine_OR.pdf

Syverson, C. (2011). What determines productivity? Journal of Economic Literature, 49 (2), 326-365. (See especially sections 3.4 on learning by doing and 4.1 on productivity spillovers). http://home.uchicago.edu/~syverson/productivitysurvey.pdf

Yelle, Louis E. 1979. The learning curve: Historical review and comprehensive survey. Decision Sciences 10.2, 302-328. http://tuvalu.santafe.edu/~bn/reading_group/Yelle.pdf

3. Learning in Mobile Source Manufacturing Sectors – Articles selected for detailed review (10 articles)

Agrawal, A., Muthlingam, S. 2015. Does organization forgetting affect vendor quality performance? An empirical investigation. Manufacturing & Service Operations Management, Articles in Advance, pp. 1-18. April 2015. http://pubsonline.informs.org/doi/abs/10.1287/msom.2015.0522

Benkard, C Lanier. 2000. Learning and Forgetting: The Dynamics of Aircraft Production. The American Economic Review, 90(4),1034-1054. http://www.econ.yale.edu/~lanierb/research/Learning_and_Forgetting_AER.pdf

Bernstein, Paul. 1988. The Learning Curve At Volvo. Columbia Journal Of World Business 23.4. 87-95. Business Source Complete. Web. 25 Nov. 2013.

Epple, Dennis, Linda Argote, and Rukmini Devadas. 1991. Organizational learning curves: A method for investigating intra-plant transfer of knowledge acquired through learning by doing. Organization Science 2.1, 58-70. http://pubsonline.informs.org/doi/abs/10.1287/orsc.2.1.58?journalCode=orsc

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Gopal, A, M Goyal, S Netessine, M Reindorp. 2013. The Impact of New Product Introduction on Plant Productivity in the North American Automotive Industry. Management Science, 59(10), 2217-2236. http://www.rhsmith.umd.edu/faculty/agopal/AutoLaunch%20MS%20Final.pdf

Lee, Jaegul, et al. 2010. Forcing technological change: A case of automobile emissions control technology development in the US. Technovation 30.4, 249-264. http://www.sciencedirect.com/science/article/pii/S0166497209001746

Levitt, Steven D., John A. List, and Chad Syverson. 2012. Toward an Understanding of Learning by Doing: Evidence from an Automobile Assembly Plant. No. w18017. National Bureau of Economic Research. http://www.nber.org/papers/w18017

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Shinoda, Yukio, et al. 2009. Evaluation of the plug-in hybrid electric vehicle considering learning curve on battery and power generation best mix. IEEJ Transactions on Power and Energy 129, 84-91. http://onlinelibrary.wiley.com/doi/10.1002/eej.21098/abstract;jsessionid=FF83CDDA7D582392635F6CB5F4F4FCCA.f03t01?deniedAccessCustomisedMessage=&userIsAuthenticated=false

4. Learning in Mobile Source Manufacturing Sectors – Articles selected for cursory review (16 articles)

Alchian, Armen. 1963. Reliability of Progress Curves in Airframe Production. Econometrica: Journal of the Econometric Society, 31, 679-693. http://www.caps.am/materials/diaspora%20writings/Reliability%20of%20progress%20curves.pdf

Argote, Linda, Sara Beckman, Dennis Epple. 1990. The persistence and transfer of learning in industrial settings. Management Science, 36(2), 140-154. http://wpweb2.tepper.cmu.edu/facultyadmin/upload/ppaper_632795255914_2661452.pdf

Bailey, M.N., Farrell, D., Greenberg, E., Henrich, J.-D., Jinjo, N. Jolles, M. & Remes, J. 2005. Increasing global competition and labor productivity: Lessons learned from the US automotive industry. Paper presented at the Federal Reserve Bank of San Francisco conference, "Productivity Growth: Causes and Consequences." Nov 18-19, 2005. http://www.mckinsey.com/industries/automotive-and-assembly/our-insights/increasing-global-competition-and-labor-productivity

Fisher, Marshall L., and Christopher D. Ittner. 1999. The impact of product variety on automobile assembly operations: Empirical evidence and simulation analysis. Management science 45.6, 771-786. http://pubsonline.informs.org/doi/abs/10.1287/mnsc.45.6.771

Fisher, Marshall, Kamalini Ramdas, Karl Ulrich. 1999. Component Sharing in the Management of Product Variety: A Study of Automotive Braking Systems. Management Science, 45(3), 297-315. http://opim.wharton.upenn.edu/~ulrich/downloads/parts.pdf

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Kim, Ilhyung, Hae Lim Seo. 2009. Depreciation and transfer of knowledge: an empirical exploration of a shipbuilding process. International Journal of Production Research, 47(7), 1857-1876. http://www.tandfonline.com/doi/abs/10.1080/00207540701499481#.UvqC4fldVHA

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MacDuffie, John Paul, Kannan Sethuraman, and Marshall L. Fisher. 1996. Product variety and manufacturing performance: evidence from the international automotive assembly plant study. Management Science 42.3, 350-369. http://pubsonline.informs.org/doi/abs/10.1287/mnsc.42.3.350

Randall, Taylor, Karl Ulrich. 2001. Product Variety, Supply Chain Structure, and Firm Performance: Analysis of the U. S. Bicycle Industry. Management Science, 47(12),1588-1604. http://www.ktulrich.com/uploads/6/1/7/1/6171812/bike-supplychains.pdf

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Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources

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Prepared for
U.S. Environmental Protection Agency
Office of Transportation and Air Quality
Assessment and Standards Division
2000 Traverwood Drive
Ann Arbor, MI 48105

Prepared by
ICF
9300 Lee Highway
Fairfax, VA 22031

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Acronyms and Abbreviations

Acronym / Abbreviation	Stands For
BEV	Battery Electric Vehicles
CARB	California Air Resource Board
CO_2	Carbon Dioxide
EPA	United States Environmental Protection Agency
DLA	Deliberate Learning Activity
FGD	Flue Gas Desulfurization
HR	Human Resource
IT	Information Technology
NO_x	Nitrogen Oxides
OTAQ	Office of Transportation and Air Quality
PHEV	Plug-In Hybrid Electric Vehicle
R&D	Research and Development
SCR	Selective Catalytic Reduction
SIC	Standard Industrial Classification
SME	Subject Matter Expert
SO_2	Sulfur Dioxide

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1. Introduction

Since the late 1990s, EPA's Office of Transportation and Air Quality (OTAQ) has included a learning effect when estimating the costs of regulatory packages. Specifically, technology costs—for technologies added to mobile sources to allow for compliance with new emissions standards—are estimated to decrease in the years following first implementation. This decrease in technology costs, either due to the volume of production or to time, is considered to be due to learning (i.e., the "learning effect").

We use the term "learning effect" to refer to the relationship between the volume of production (i.e., cumulative output) and unit costs. Cumulative output is a measure of experience gained in production. Just as individuals have been found to benefit from their experience, groups and organizations have also been found to benefit from the experience they acquire. Learning can reflect efficiencies gained in production processes, improvements in tooling and in the design of the manufactured components, increased proficiency of individual employees, and improvements in the organization's structure or some combination of these factors. This learning effect has been studied by academia and industry for more than 60 years. Many studies are available that examine the learning effect, or aspects of it; the vast majority of these studies conclude that cost reductions through learning do, in fact, occur. Other studies assume that cost reductions will occur based on the body of evidence suggesting that they do and incorporate learning effects into their analysis, as EPA does in its cost analyses.

The relationship between experience and performance has been documented in both laboratory and field studies. Laboratory studies are high in internal validity and enable one to establish causality while field studies are high in external validity and enable one to estimate the effects of variables in realistic conditions (Croson, Anand, & Agarwal, 2007). For purposes of the current project, we focus our review on field studies of the relationship between cumulative output and unit costs. The evidence of an effect of experience on performance in laboratory studies (Argote, Insko, Yovetich, & Romero, 1995; Guetkow & Simon, 1955) increases our confidence that experience has a causal effect on performance indicators, such as unit costs.

While there is little doubt that this learning effect occurs, the learning estimates used by OTAQ in its recent cost analyses are based on somewhat dated studies that are not specific to the mobile source sector. Therefore, EPA tasked ICF with a work assignment[1] that would involve conducting an assessment of learning covering most notably the automotive industry (both original equipment manufacturers and Tier 1 suppliers). In addition to studies of learning for the light-duty vehicle sector and automotive parts suppliers, the scope of the learning assessment would cover other on-road mobile source industries, such as manufacturing of loose engines (i.e., those built for installation in large highway trucks and/or non-road equipment), manufacturing of large vocational and line-haul trucks, and manufacturing of large non-road equipment. This work would provide a definitive, up-to-date, reliable, single source of information evaluating the occurrence of learning in the mobile source industries. It would also summarize empirical estimates of the learning effect separately for each of the specific mobile source industries (e.g., original equipment auto makers, parts suppliers to those auto makers, loose engine

[1] EPA Contract EP-C-12-011 Work Assignment 3-09.

manufacturers, large truck manufacturers, and non-road equipment manufacturers) for which studies are found that address those specific sectors. Finally, using that information, the study would provide an estimate of learning effects for each of the separate mobile source industries for which published data exists.

As explained in more detail in Section 2, the literature did not support the development of unique estimates for the separate mobile source industries because very few studies have been published on learning in mobile source industries outside of the automotive industry. This could be due to the confidential nature of the data that would be necessary to conduct such a study. Such data are typically viewed as proprietary and are not publically available. It would be very difficult to obtain permission to combine such proprietary data with those from other firms and competitors for the purpose of such a study. For this reason, this report provides EPA with a single learning rate for the whole mobile source sector at the organizational (i.e., plant) level, rather than for specific mobile source industries.

Although the literature did not support the development of unique estimates for separate mobile source industries, it did support the development of estimates of the rate of organizational learning in the mobile source sector generally. Therefore, this report aims to meet three objectives: (1) to be a definitive, up-to-date, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically; (2) to develop a single compendium study on industrial learning in the mobile source sector that could be considered for use in future OTAQ costs analyses; and (3) to develop a summary effect of learning based on cumulative output in mobile source industries. By developing a summary effect, we mean that we will aggregate learning rates—more specifically, progress ratios—found in relevant articles to come up with a single mobile source progress ratio for EPA to consider for use in future OTAQ cost analyses.

This report provides an assessment of learning, both generally and as it relates to the mobile source industry through a review of 18 published studies on learning curves. In Section 2, we describe the methodology used to identify studies that form the basis of the analysis. Section 3 contains a summary of the analysis and recommended progress ratio for the mobile source industry. Section 4 contains detailed summaries of the 18 studies reviewed by topic. There are 4 appendices to this report. Appendix A describes two methods that can be used for estimating the impacts of learning. Appendix B provides notes on the 18 articles that received a detailed review and are discussed in Section 4. Appendix C provides notes on the 16 articles that apply to the mobile source sector and received a cursory review. Appendix D contains responses to comments that were provided in a separate peer review process undertaken by EPA.

2. Selection of Subject Matter Expert and Identification of Relevant Learning-Related Studies

EPA engaged ICF to perform an assessment of learning as it relates to manufacturing sectors generally and mobile source industries specifically. The assessment would consist of a literature review of studies of learning in mobile source industries and would identify empirical estimates of learning from those studies, as well as studies of learning in general manufacturing to provide background and context for the literature review. The goals of the assessment are to develop (1) a definitive, up-to-date, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically; (2) a single compendium study on industrial learning in the mobile source sector that could be considered for use in future OTAQ costs analyses; and (3) an estimated summary effect of learning in mobile source industries.

Because of the specialized nature of this project, EPA requested ICF seek the assistance of a subject matter expert (SME). To identify the SME, ICF searched university websites to find academic researchers who had published extensively in the field of manufacturing learning curves as it related to automotive and mobile source equipment industries. This resulted in eight possible candidates who included: (1) Dr. Linda Argote of Carnegie Mellon University; (2) Jamie McCarthy of the Boston Consulting Group; (3) Dr. Pete Klenow of Stanford University; (4) Dr. Edward S. Rubin of Carnegie Mellon University; (5) Dr. George Day of the University of Pennsylvania; (6) Dr. Birger Wernerfelt of the MIT Sloan School of Management; (7) Dr. David B. Montgomery of Stanford University; and (8) Dr. Marvin Lieberman of the University of California, Los Angeles. Dr. Argote expressed an interest in this project and was selected because of her expertise and extensive publications in the area of automotive manufacturing learning curves.

At the same time, ICF conducted a preliminary literature search to identify articles that examine learning curves in the manufacturing sectors generally and in mobile source manufacturing specifically. Initially, this list was developed by researching various academic journals in economics such as *The Journal of Industrial Economics*, the *Journal of Economic Literature*, *The American Economic Review*, the *Journal of Political Economy*, and *The RAND Journal of Economics* as well as in management, such as *Management Science*, *Organization Science*, and the *International Journal of Production Research*. Next, articles published by the eight SME candidates were added to the list. Priority was given to articles published since 1990 and those related to mobile source industry manufacturing. ICF obtained the selected articles and examined the reference list of each article for additional articles on manufacturing learning curves in general and in mobile source manufacturing specifically. The reference lists of the additional articles were also reviewed and articles were further added to the list. The literature review includes studies spanning many years, but whenever possible ICF attempted to capture studies published since 1990 in order to identify recent estimates of learning rates. Lapré and Nembhard (2010) provided a strong review of the recent literature that was also culled for additional sources.

The initial list was sent to the SME, Dr. Argote, for review. Based upon her extensive knowledge on the subject matter and the literature she reviewed for the second edition of her book, *Organizational*

Learning: Creating, Retaining and Transferring Knowledge (Argote, 2013), she added 11 studies relevant to learning curves in manufacturing sectors generally and 16 studies for mobile source industries specifically.

Dr. Argote provided ICF with the revised list of studies. After consultation with ICF, a list with the combined search results was provided to EPA for review and approval. The reference list contained 26 studies related to manufacturing sectors generally and 23 studies for mobile source industries specifically. EPA added several articles to the list based upon their extensive research on the subject. Based on EPA's feedback, the reference list was divided into four sections: studies of learning curves in general and studies of learning curves in the mobile source sector, with those two sets of studies selected for either a detailed review or a cursory review.

The list was further refined as new articles were published. For example, EPA identified an article published online in *Nature* on March 23, 2015 (Nykvist & Nilsson, 2015) and Dr. Argote identified an article forthcoming in *Manufacturing & Service Operations Management* (Agrawal & Muthulingam, 2015) that were relevant. After discussion with EPA, both articles were added to the reference list. Furthermore, Dr. Argote consulted other learning curve SMEs about potential studies and thereby identified two additional studies. After discussions with EPA, one of these studies was added to the reference list (Levin, 2000). Dr. Argote concluded that this selection of published materials would be sufficient to support the development of robust observations about learning in mobile source industries.

Peer reviewers of this report identified three additional articles that should be considered (Balasubramanian & Lieberman, 2011; Haunschild & Rhee, 2004; and Hendel & Spiegel, 2014). After discussion with EPA, these articles were added to the reference list as well.

The final reference list consists of eight articles of learning curves in general, selected for a detailed review. The 21 other articles of learning curves in general were selected for a cursory review. Ten articles of learning curves in the mobile source sector were selected for a detailed review. The additional 16 articles of learning curves in the mobile source sector were selected for a cursory review. The overarching criterion for selecting articles for a detailed review was to focus on articles that provided empirical estimates of learning rates that could be used in future cost estimates for the mobile source sector. Thus, we focused on studies containing empirical estimates of learning in contemporary production environments. For example, six of the studies in the reference list for mobile source manufacturing were based on analyses of Liberty ship production during World War II (Rapping, 1965; Argote, Beckman, & Epple, 1990; Kim & Seo, 2009; Thompson, 2007; Thompson, 2001; and Thornton & Thompson, 2001). Although five of these studies were published since 1990, their empirical estimates of learning were based on historical data from a unique context and thus, are less useful for our purposes than estimates based on more contemporary data.

There is general agreement across this literature that learning occurs in organizations in general and in mobile source industries in particular (see Argote, 2013; Balasubramanian & Lieberman, 2010; Dutton & Thomas, 1984; and Lapré & Nembhard, 2010, for reviews). Thus, the articles in the reference list provide strong evidence that learning occurs in firms in the mobile source industry.[2]

Although the literature supports the development of estimates of the rate of organizational learning in the mobile source sector, the literature does not support the development of different estimates for separate mobile source industries.[3] Multiple studies of organizational learning have been conducted at plants in the automotive industry; however, fewer studies have been done on learning in other mobile source industries. This may be due to the confidential nature of the data that would be necessary to conduct such a study. Such data are typically viewed as proprietary and are not publically available. It would be very difficult to obtain permission to combine such proprietary data with those from other firms and competitors for the purpose of a study of learning for a particular mobile source industry. As a result, there is not enough information in published studies to support the development of different rates of learning for separate mobile source industries. However, this may not be important for EPA's work and there is good reason to believe that a rate of learning estimated at the mobile source industry level may be applied to the separate sub-industries. Based on a review of the literature on learning effects across different organizational contexts, Argote (2013) concluded that the biggest difference in learning rates was between manufacturing and service sectors, with organizations in the manufacturing sector learning at a faster rate than those in the service sector. In addition, an earlier review focused on learning curves in manufacturing industries did not find evidence of industry effects (Dutton & Thomas, 1984). Based on the available evidence to date and because all of the mobile source industries are in the manufacturing sector, it would be reasonable to use the same learning rate for different mobile source industries.

[2] One of the peer reviewers stated that overall approach to the literature (i.e., identifying studies of learning-by-doing in the mobile source sector, reviewing them for relevance to the study's goals, and identifying a shorter list of relevant articles) appears reasonable. The peer reviewer stated that the list of topics included in Section 4 of the report and the coverage of those topics appears broadly reasonable. See Appendix D for the full comments.

[3] One of the peer reviewers stated that the overall conclusion that learning-by-doing occurs in the mobile source sector is well-founded and largely indisputable. See Appendix D for the full comments.

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3. Review of Learning Curves and Progress Ratios and a Summary of Results and Recommendations

As discussed in the Introduction, this report aims to meet three objectives: (1) to be a definitive, up-to-date, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically; (2) to develop a single compendium study on industrial learning in the mobile source sector that could be considered for use in future OTAQ costs analyses; and (3) to estimate a summary effect of learning based on cumulative output in mobile source industries. In Section 3.1 and 3.2, we provide background information about learning curves and progress ratios, respectively. In Section 3.3, we provide a summary of the 18 studies on learning in general and in the mobile source sector specifically that we included in our literature review. In Section 3.4, we discuss the results of our review and, on the basis of that review provide an estimated progress ratio for the mobile source industry.

3.1. What are Learning Curves?

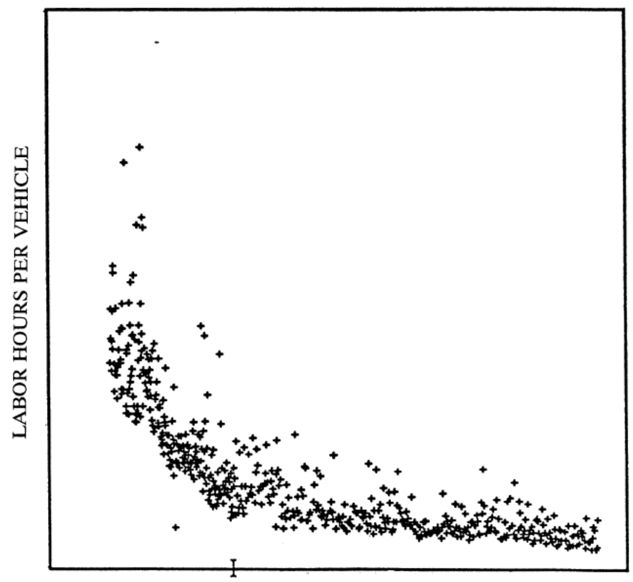
A learning curve represents a fundamental relationship: as a person or organization does more of something, it gets better at doing it. More specifically, "as organizations produce more of a product, the unit cost of production typically decreases at a decreasing rate" (Argote, 2013, p. 1). Research in organizational and manufacturing learning builds on research in psychology, where it was demonstrated that error rates and time to complete tasks decrease with experience (Argote, 2013).

Learning is an important source of productivity improvements in organizations. Organizations that are able to learn more from experience enjoy greater productivity and greater prospects of survival than their counterparts that are less adept at learning (Argote & Ingram, 2000; Baum & Ingram, 1998). Estimates of learning are used in many applications in organizations, including forecasting production, purchasing, making delivery commitments, monitoring performance, determining manufacturing strategy, pricing, and deciding about whether to enter a new market.

Although individuals are the mechanism through which organizations learn, organizational learning involves more than learning by individuals. In order for learning to be considered organizational, it should be embedded in a supra-individual repository, such as a routine or process, a database, a template, or a tool or technology. Thus, organizational learning can be embedded in individual employees, including managers and engineers as well as direct production workers, in tools and technologies, and in routines and processes.

Figure 1 shows an example of a learning curve based on data from the start of production of a new model at a truck plant. Cumulative output, the cumulative number of trucks produced, is plotted on the horizontal axis. The labor hours required to assemble each truck is plotted on the vertical axis. The figure illustrates the classic learning curve: labor hours per vehicle decrease at a decreasing rate as experience is gained in production. While many researchers have focused on labor costs, others have included additional costs, such as material costs (e.g., Balasubramanian & Lieberman, 2010; Darr, Argote & Epple, 1995) and found that these measures also evidence learning.

Intuitively, there is more to learn at the beginning of production. Employees have to learn their individual tasks and how to coordinate their tasks with others' tasks. Routines are developed. The layout is improved and tools are modified to improve their performance. Hence, the learning at the beginning of a production program is steeper than learning later in the production program, where it takes longer to double cumulative output.



Note: Reprinted from Epple, Argote, & Murphy (1996)

Figure 1. Learning Curve for the Truck Plant

The conventional form of a learning curve is a power function:

$$y_t = a\, x_{t\text{-}1}^{b} \qquad \text{(Eq. 1)}$$

Where:

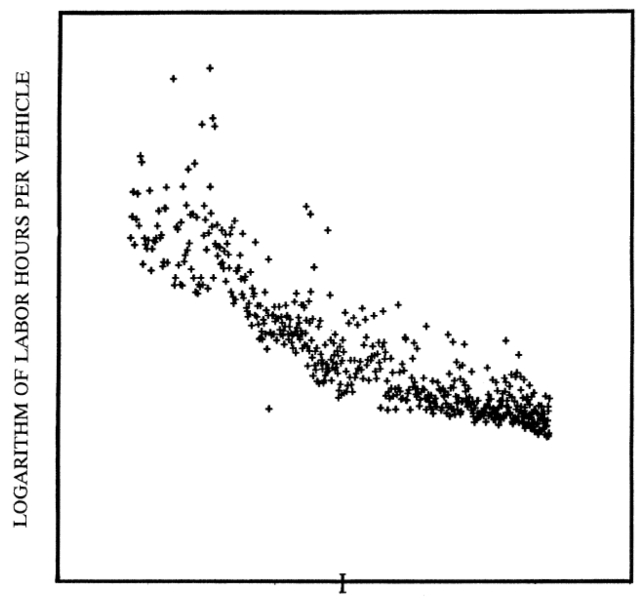
x_t	=	Cumulative number of units produced by an organization (i.e., experience gained) by date t
y_t	=	Costs required to produce an additional unit at date t
a	=	Costs required to produce the first unit
b	=	Parameter that measures the rate unit costs change as cumulative output increases. If learning occurs, b<0.
t	=	Time subscript

While learning curves are typically expressed as the relationship between costs per unit and production volume, other dependent measures have been used including the amount of time it takes to produce a unit of output, defects per unit, or accidents per unit. The particular dependent measure used depends on the researcher's purpose. Our focus in this report is on unit costs.

Equation 1 can be rewritten in logarithmic form:

$$\ln(y_t) = a + b \ln(x_t) \qquad \text{(Eq. 2)}$$

Figure 2 shows the same relationship depicted in Figure 1 in logarithmic form. As can be seen from Figure 2, when the data are plotted using a log-log scale, the relationship is closer to a straight line.



Note: Reprinted from Epple et al. (1996).

Figure 2. Logarithm of Direct Labor Hours per Vehicle versus Logarithm of Cumulative Hours

The cumulative number of units produced (also referred to as cumulative output or cumulative volume) measures how much experience the organization has acquired in production. The measure is computed by adding the number of units produced from the start of production through the end of the previous time period. If unit costs change as a function of experience, other factors equal, then learning has occurred.

Other variables that are likely to affect the outcome variable can be added to the equation in order to control for explanations alternative to learning, such as economies of scale. In addition, one can investigate whether the rate of learning slows down or plateaus by including a quadratic term for the cumulative output variable. Including a quadratic function for the experience variable and evaluating it at values less than the value at which the function reaches a minimum, approximates a function with a positive asymptote, and thus allows one to investigate whether the rate of learning slows down in logarithmic form.

Debate has occurred about whether cumulative output or the amount of time that an organization has produced a product is the better measure of experience to use in investigations of learning. Several studies that have included both cumulative output and time found that cumulative output was significant but time was not (Rapping, 1965; Lieberman, 1984). Other studies that have included both time and cumulative output reported that both were significant but that the magnitude of the regression coefficient on the cumulative output variable was greater than that on the time variable (Argote, Epple, Rao, & Murphy, 1997 as cited in Argote, 2013[4]; Bahk & Gort, 1993). Benkard (2000) included both cumulative output and time as well, and although the fit improved when the time variable was included, the sign of the time variable was negative; hence, the model was rejected. Levitt, List, and Syverson (2013) found that the time trend was small in magnitude and only marginally significant when included in a model with cumulative output. Yet, Levin (2000) found that time was a more important source of improvement in the quality of cars than cumulative output because the significance of the cumulative output variable disappeared once year-of-production variables were taken into account. On balance, researchers have concluded that learning is more related to production activity, as measured by cumulative output, than to the passage of time.

As described in more detail in the following sections, researchers have also attempted to unpack the relationship between cumulative output and cost by investigating factors such as organizational forgetting and knowledge transfer or spillover (i.e., learning from the experience of other organizational units). Equations 1 and 2 can be generalized to investigate these issues. Results of investigating these issues are summarized in our literature review in Section 4.

3.2. What are Progress Ratios?

Organizations often characterize their learning rates in terms of a progress ratio, p, which describes how the outcome variable changes when cumulative output doubles. For example, the interpretation of an 80% progress ratio is that for every doubling of cumulative output, the outcome variable (e.g., costs per unit in Equation 1) declines to 80% of its previous value. An 80% progress ratio means that costs decline by 20%. Thus, lower progress ratios imply faster learning because costs are declining at a faster rate.

A progress ratio, p, can be computed from the learning rate, b, as follows:

y_1 = Unit cost after producing x_1 units

y_2 = Unit cost after producing $2x_1$

$y_1 = a\, x_1^b$

$y_2 = a\,(2x_1)^b$

[4] We referenced the description in the Argote (2013) book because the Argote et al. (1997) article has not been published due to its use of proprietary information.

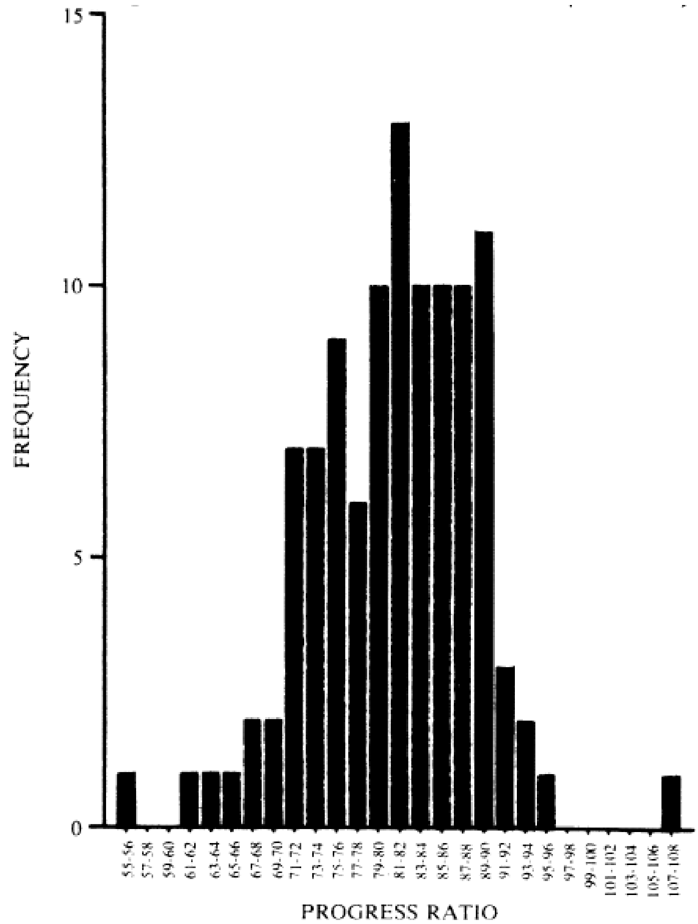
$$p = \frac{y_2}{y_1} = 2^b \qquad \text{(Eq. 3)}$$

Conversely, the learning rate, b, can be computed from the progress ratio, p:

$$\ln(p) = b \ln(2)$$

$$b = \frac{\ln(p)}{\ln(2)} \qquad \text{(Eq. 4)}$$

In a seminal study often cited in the industrial and manufacturing learning literature, Dutton and Thomas (1984) examined progress ratios estimated from 108 production programs that covered manufacturing processes in several industries as reported in 22 field studies (see Section 4.1.1, below). These authors used only progress ratios that were estimated using either unit costs or average costs as the outcome variable and cumulative volume as the independent variable and excluded studies estimating industry-wide estimates. The authors constructed a histogram, reproduced in Figure 3, illustrating their results. Several conclusions can be drawn from the histogram. First, the rate of learning varies across organizations. Second, although the rate of learning varies, all but 1 of the 108 production programs improved with experience. Third, the mode of the progress ratios was between 81% and 82%. This implies that for every doubling in cumulative output, unit costs decrease to 81% or 82% of their former value.



Note: Reprinted from Dutton and Thomas (1984).

Figure 3. Distribution of Progress Ratios Observed in 22 Field Studies (N=108)

3.3. Summary of Literature Review

An objective of this report was to provide a definitive, up-to-date, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically and to develop a single compendium study on industrial learning in the mobile source sector that could be considered for use in future OTAQ cost analyses. In addition to providing background and context about learning, we were particularly interested in identifying empirical estimates of progress ratios in the literature.

In total, we reviewed 55 articles related to learning, of which 18 articles were reviewed in detail mainly because they contained empirical estimates of learning in contemporary production environments (see Section 2). The 18 articles cover several industries in the mobile source sector (e.g., cars, electric vehicles, trucks, aircraft, and wartime ships) and some outside the mobile source sector (e.g., fast food, electric power plants, and the manufacturing sector in general). The research method varied among these articles. Most research was quantitative; however, some authors made valuable insights using qualitative methods. Similar to Figure 2 above, we found that the rate of learning varies, albeit not as much as shown in Figure 3. The estimated progress ratios found in the 18 articles ranged from 70% to 98%. These 18 articles represent a range of research conducted over the last 30 years and provide strong evidence that learning occurs in the mobile source industry and in general.

The articles we reviewed support the claim that learning is a major source of productivity improvements in organizations. In addition, learning is a source of competitive advantage for firms (Balasubramanian & Lieberman, 2010). Firms that are able to learn from experience and transfer the knowledge they acquire throughout their establishments are more productive and more likely to survive than their counterparts that are less adept at organizational learning. Thus, organizational learning is of great importance to managers as well as to policy makers. Learning enables organizations to be more productive and competitive. An understanding of learning enables organizations to perform a host of activities more effectively, including planning, budgeting, production scheduling, making delivery commitments, and monitoring performance.

Learning occurs through individuals in organizations. Not only direct production workers but also managers, engineers, and support staff learn as an organization gains experience in production. Individuals become better at their particular jobs and also better at coordinating their tasks with those of other employees. Improvements are discovered in the technology (both hardware and software) and layout of the plant. Routines and processes are modified to become more efficient and the structure of the organization is fine-tuned to enable more effective problem solving. Thus, knowledge acquired by learning by doing in organizations is embedded in individual employees and in the organization's technology, routines, and structure.

Table 1 presents a summary of 21 articles of which 18 are included with detailed review in this study, and are subsequently described in the next sections and are summarized in Appendix B. Table 1 provides the following information:

- *Column 1 – Article citation*: Column 1 provides the authors' names and the years of publication. It also lists the sections in which the article is discussed within this report. Several articles (i.e., Argote et al., 1990; Argote et al., 1997 as cited in Argote, 2013; and Darr, Argote, & Epple, 1995) were not selected for detailed review, but were described in articles that were reviewed in detail or received a cursory review; hence, these articles are not discussed in the sections below.
- *Column 2 – Type of Analysis (Qualitative vs. quantitative)*: The progress ratios presented include only those from studies that analyzed original data. Therefore, progress ratios are not featured for the few studies that are solely qualitative reviews or thought pieces (which are highlighted in the table). If the qualitative analysis mentioned progress ratios that were estimated in other studies, those progress ratios are listed in the table under their original authors' names. These studies include Argote et al. (1990); Argote et al. (1997) as cited in Argote (2013); and Darr et al. (1995).

- *Column 3 – Type of Data (Primary vs. secondary)*: Column 3 lists whether each study was based on primary, or secondary data[5]. For example, the progress ratios in Nykvist and Nilsson's (2015) study were estimated using estimates from other studies rather than primary data.
- *Column 4 and 5 – Type of Industry*: Column 4 lists the industry that was the focus of the article and Column 5 describes whether the industry belongs to the mobile source sector.
- *Column 6 – Type of Outcome Variable*: Column 6 lists the outcome variable used to estimate the progress ratio. Many studies use unit costs or a related variable; the number of units produced which can be expressed in terms of unit costs. Several studies used other outcome variables such as shipments (see Bahk & Gort, 1993), real value added (see BahK & Gort, 1993; Balasubramanian & Lieberman, 2010), and price (see Shinoda, Tanaka, Akisawa, & Kashiwagi, 2009). These others measures are not appropriate for the goals of this study: Output measured by shipments would not be a good measure of productivity if firms keep output in inventory before shipping. Output measured in terms of dollar value as well as measures of value added are based on revenues, which are affected by many factors besides learning in manufacturing; and prices are affected by external conditions. As one of our reviewers noted, using any measure that embodies price is likely to confound supply-side learning (our focus) with demand-side changes that might be unrelated to learning. We focus on studies using unit costs, the number of units produced, or defects per unit because these variables are the most closely related to costs in mobile source manufacturing. For studies using the number of units produced as the dependent variable (Argote et al., 1997; Epple et al., 1991; Epple et al., 1996), the models were re-estimated with costs per unit as the dependent variable.
- *Column 7 and 8 – Type of Progress Ratio (Cumulative output vs best fit)*: For each study, we list the progress ratio based on a model using only cumulative output and the progress ratio based on the model with the best fit according to the adjusted R^2 value presented in the study. The models that use only cumulative output are more comparable across studies and to previous reviews, such as the Dutton and Thomas (1984) review described earlier in Section 3.2. Researchers had different goals in the various studies so they included different variables in their models in addition to cumulative output, depending on the purpose and empirical context of the study. Many studies had the goal of dissecting the relationship between cumulative output and cost into different components. Because our goal is to develop a reliable estimate of the effect of cumulative output, we focus on models that include only cumulative output as a predictor.

[5] We consider primary data to be data collected by a study's researcher directly and secondary data to be data collected by or produced by a different study.

Table 1. Summary of Progress Ratios in Sample

Author(s) and Publication Date	Qualitative/ Quantitative	Primary/ Secondary Dataset	Industry	Mobile Source Industry? (Y = Yes, N= No)	Outcome Variable	Progress Ratio (Cumulative Output Approach)	Progress Ratio (Best-Fit Approach)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agrawal & Muthulingam (2015) See Sections 4.2.5 and 4.4.3 below	Quantitative	Primary	Car manufacturer vendors	Y	Defect rate	N/A[a]	N/A
Argote (2013) See Section 4.2.3 below	Qualitative	Secondary	N/A	N	N/A	N/A	N/A
Argote, Beckman, & Epple (1990)	Quantitative	Secondary	Wartime ships	Y	Current output (i.e., tonnage of ships produced per month)	74%	97%
Argote & Epple (1990) See Section 4.1.2 below	Qualitative	Secondary	N/A	N	N/A	N/A	N/A
Argote, Epple, Rao, & Murphy (1997) as cited in Argote (2013)	Quantitative	Primary	Trucks	Y	Current output	86%[b]	83%
Bahk & Gort (1993) See Section 4.4.4 below	Quantitative	Primary	A pool of 15 industries	N	Output measured by shipments	97%	95%
			Motor vehicle parts, accessories	Y		98%	98%
			A pool of 41 industries	N		95%	95%

Author(s) and Publication Date	Qualitative/ Quantitative	Primary/ Secondary Dataset	Industry	Mobile Source Industry? (Y = Yes, N= No)	Outcome Variable	Progress Ratio (Cumulative Output Approach)	Progress Ratio (Best-Fit Approach)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Balasubramanian & Lieberman (2010) See Section 4.1.4 below	Quantitative	Primary	U.S manufacturing sector	N	Current period real value added (i.e., real revenues less real materials)	84%	86%
			Motor vehicles and equipment	Y		88%	88%
			Aircraft and parts	Y		90%	90%
			Ship and boat building and repairing	Y		93%	93%
			Railroad equipment	Y		91%	91%
			Motorcycles bicycles and parts	Y		89%	89%
			Misc. transportation equipment	Y		94%	94%
Benkard (2000) See Sections 4.2.2 and 4.3.2 below	Quantitative	Primary	Aircraft (commercial)	Y	Labor input per unit	82%	65%
Bernstein (1988) See Section 4.5.1 below	Qualitative	N/A	Automobiles	Y	N/A	N/A	N/A
Darr, Argote, & Epple (1995)	Quantitative	Primary	Fast food industry	N	N/A	93%	93%

Author(s) and Publication Date	Qualitative/ Quantitative	Primary/ Secondary Dataset	Industry	Mobile Source Industry? (Y = Yes, N= No)	Outcome Variable	Progress Ratio (Cumulative Output Approach)	Progress Ratio (Best-Fit Approach)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dutton & Thomas (1984) See Section 4.1.1 below	Qualitative	Secondary	A variety of industries (e.g., electronics, machine tools, papermaking, aircraft, steel, and automobiles)	N	N/A	N/A	N/A
Epple, Argote, & Devadas (1991) See Sections 4.3.1 and 4.4.1 below	Quantitative	Primary	Trucks	Y	Output during week t	87%[b]	35%
Epple, Argote, & Murphy (1996) See Section 4.2.1 below	Quantitative	Primary	Trucks	Y	Output during week t	86%[b]	66%
Gopal, Goyal, Netessine, & Reindorp (2013) See Section 4.2.4 below	Quantitative	Primary	N/A	N	N/A	N/A	N/A
Lapré & Nembhard (2010) See Section 4.1.5 below	Qualitative	Secondary	Manufacturing and service industries	N	N/A	N/A	N/A
Lee, Veloso, Hounshell, & Rubin (2010) See Section 4.5.4 below	Qualitative and Quantitative	Primary	Automobiles; automobile emission control technologies; specifically, non-catalyst components	Y	Cost of non-catalyst components	93%	93%

Author(s) and Publication Date	Qualitative/ Quantitative	Primary/ Secondary Dataset	Industry	Mobile Source Industry? (Y = Yes, N= No)	Outcome Variable	Progress Ratio (Cumulative Output Approach)	Progress Ratio (Best-Fit Approach)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Levitt, List, & Syverson (2013) See Sections 4.3.3 and 4.4.2 below	Quantitative	Primary	Automobiles	Y	Average defect for the week	82%	80%
Macher & Mowery (2003) See Section 4.1.3 below	Quantitative	Primary	Semiconductors	N	Defect density (i.e., the number of fatal defects per centimeter squared)	N/A[a]	N/A
Nykvist & Nilsson (2015) See Section 4.5.5 below	Quantitative	Secondary	Battery electric vehicles (industry-wide)	Y	Cost data	91%	91%
Rubin, Taylor, Yeh, & Hounshell (2004) See Section 4.5.2 below	Quantitative	Unclear	Electric power plants; FGD systems	N	Cost to produce the *i*th unit	89%	89%
			Electric power plants; SCR systems	N	Cost to produce the *i*th unit	88%	88%
Shinoda, Tanaka, Akisawa, & Kashiwagi (2009) See Section 4.5.3 below	Quantitative	Primary	Plug-in hybrid electric vehicles	Y	Battery unit price	70%	70%

Notes:

a. The authors did not estimate learning using the power function; hence, their learning rates could not be converted to progress ratios as described in the text.

b. The papers did not provide estimates of costs per unit as a function of cumulative output. Because the SME was a coauthor on these papers, she was able to estimate the learning rate when the dependent measure was costs per unit and the predictor was cumulative output.

3.4. Discussion of Mobile Source Results and Recommendations

The report's third goal was to develop a summary effect of learning based on cumulative output in mobile source industries. We used several criteria to determine the summary effect of learning on costs in mobile source industries. We relied on studies that were primary analyses of data from firms in the mobile source sector whose methods were quantitative and statistically sound. We did not include studies that based their estimates on only a very small number of observations (e.g., Lee et al., 2010; Nykvist and Nilsson, 2015; and Rubin et al., 2004). Because the focus of our analysis is on manufacturing costs, we included studies that used unit costs or variables closely related to costs, such as the number of units produced or defects per unit, as the dependent variable. Finally, while many studies analyzed data from the production of ships during World War II, we did not use these estimates because of the studies' unique empirical context (e.g., exceptionally high motivation due to the need to build ships for the war effort and coordination across firms by the U.S. Maritime Commission).

Note that in its regulatory packages, OTAQ has accounted for learning when estimating the technology costs for technologies added to mobile sources to allow for compliance with new emission standards. Our extensive search of the learning curve literature indicates that the literature has not focused on learning at the individual emission technology level (e.g., learning with respect to the manufacture of catalytic converters, evaporative control canisters, oxygen sensor, etc.). Instead, published studies typically examine learning at the final assembly stage of transportation equipment. Because organizations in the mobile source sector use the same type of labor and processes, assembly at the final vehicle assembly stage is substantially similar to assembly at the subcomponent level (e.g., automobile component assembly). As noted previously, the biggest and most reliable difference in learning rates was found between the manufacturing and service sectors (Argote, 2013). All firms in the mobile source industry are in the manufacturing sector. Based on the available evidence as well as the similarity of firms in the mobile source industry, they would not be expected to differ dramatically in their learning rates. Thus, we use findings from the final assembly stage to develop recommendations about learning effects in mobile source industries.

In Table 2, five studies' progress ratios are reproduced (i.e., Argote et al., 1997 reported in Argote, 2013; Benkard, 2000; Epple, Argote, & Devadas, 1991; Epple et al., 1996; and Levitt et al., 2013). These five studies met the criteria described in the previous paragraphs and thus form the basis for our recommendation about learning effects and progress ratios in the mobile source sector.

Table 2. Confidence Intervals of Progress Ratios from Selected Studies[a]

Author (Publication Date)	Industry	Progress Ratio (Cumulative Output Approach)	Confidence Interval	Learning Coefficient	Standard Error of Coefficient
(1)	(2)	(4)	(5)	(6)	(7)
Argote, Epple, Rao, & Murphy (1997) as cited in Argote (2013) See Appendix B below for a detailed summary (p. 64)	Trucks	86%	(85%, 87%)	-0.221	0.007
Benkard (2000) See Appendix B below for a detailed summary (p. 81)	Aircraft (commercial)	82%	(80%, 84%)	-0.290	0.020
Epple, Argote, & Devadas (1991) See Appendix B below for a detailed summary (p. 90)	Trucks	87%	(85%, 90%)	-0.197	0.021
Epple, Argote, & Murphy (1996) See Appendix B below for a detailed summary (p. 93)	Trucks	86%	(85%, 86%)	-0.226	0.007
Levitt, List, & Syverson (2013) See Appendix B below for a detailed summary (p. 110)	Automobiles	82%	(81%, 83%)	-0.289	0.007

Note:
a. To facilitate comparison across studies, models in studies using output as the dependent variable (Argote et al., 1997; Epple et al., 1991; Epple et al., 1996), were re-estimated with labor costs per unit as the dependent variable.

As can be seen from Column 4 in Table 2, estimated progress ratios are very similar: 82% at an automotive plant (Levitt et al., 2013), 82% at an aircraft assembly plant (Benkard, 2000), 86% at two different light-duty truck plants (Argote, et al., 1997 as cited in Argote, 2013; Epple et al., 1996)[6], and

[6] The papers did not provide estimates of the learning rate with just cumulative output as a predictor. Because the SME was a coauthor on both papers, she was able to compute the learning rate when just cumulative output was included.

87% at a third light-duty truck plant (Epple et al., 1991). Thus, the estimated progress ratios fall in a narrow range between 82% and 87%. Based on the learning rates and standard errors provided in the papers, 95% confidence intervals around these estimates of progress ratios were calculated and are presented in Table 2.

The estimated progress ratios from these five mobile source studies based on cumulative output are similar to—but slightly higher than—the Dutton and Thomas (1984) results, which are also based on cumulative output and where the most frequently observed progress ratio was between 81% and 82%. For the models just including cumulative output, two production programs in the mobile source industries had progress ratios of 82%, two had progress ratios of 86% and one had a progress ratio of 87%.

The progress ratios from the best-fitting models (see Column 8 in Table 1) were significantly different for three of the five studies: 35% at a truck plant (Epple et al., 1991), 64% at an aircraft producer (Benkard, 2000), and 66% at a different truck assembly plant (Epple et al., 1996). The best-fit approach yielded similar results to the cumulative output approach for two of the studies: 80% at an automotive plant (Levitt et al., 2013) and 83% at a third truck plant (Argote et al., 1997). These differences can be explained by the fact that the best-fitting models have more explanatory variables than just cumulative output, and the additional explanatory variables that were included differ from one study to another, depending on the goals of the research.

In order to arrive at an estimate of the average progress ratio, we computed a weighted mean, where the weight assigned to the estimate in each study was the inverse of the study's variance (see Borenstein, Hedges, Higgins, & Rothstein, 2009). For estimation purposes, we used the coefficients of cumulative output and their standard errors. These are also shown in Table 2. The weight assigned to the estimated coefficient from a study is the inverse of the estimated variance of that coefficient. The weighted mean from a set of studies is obtained by: (1) calculating the sum of the product of the weights times the estimated coefficients, and (2) dividing the result in (1) by the sum of the weights. The estimated standard error of the weighted mean is the inverse of the square root of the sum of the weights (Borenstein, et al., pages 65-66). This approach gives less weight to studies with higher standard errors.[7] Thus, the Benkard (2000) and the Epple et al. (1991) studies receive less weight than the other three studies.

The mean learning rate is estimated to be -0.245, with a standard error of 0.0039.[8] Thus, the lower bound for a 95% confidence interval for the learning rate is -0.253; the upper bound is -0.238.[9] These estimates translate into a mean progress ratio of 84.3%. The confidence interval around this number

[7] One of the peer reviewers commented that the methodology used for estimating the weighted-average progress ratio from the five studies is broadly reasonable. Given the report's objects, it appeared reasonable to focus only on studies that examine unit costs, to exclude studies that use a different measure of performance, and to exclude studies of learning-by-doing in shipbuilding during World War II due to the uniqueness of the context. See Appendix D for the full comments.

[8] We estimated the standard error as the square root of the inverse of the sum of the weights.

[9] The lower bound of the confidence interval (-0.253) is calculated as the mean (-0.245) minus the margin of error (0.008). The margin of error is the product of the standard error (0.0039) and the critical value according to a t-distribution (1.96). The upper bound (-0.238) is calculated as the mean plus the margin of error.

ranges from 83.9% to 84.8%, suggesting that one can be reasonably confident that the progress ratio falls in this interval. Thus, the summary effect of the progress ratio in mobile source industries is 84%. Our estimate of the summary effect is based on the standard approach used in meta-analysis for combining information across studies (Borenstein et al. 2009). Lieberman, one of our reviewers, concluded that our estimates are substantially in line with the learning rates Balasubramanian and Lieberman (2010) found for the mobile source sector (see Balasubramanin & Lieberman, 2011, for similar results using more fine-grained data).

Further information regarding results and the analysis can be found in Section 5 which contains responses to peer review comments directed at the analysis and results.

4. Review of Learning Curve Literature by Topic

As described in Section 2, ICF and the SME identified 18 studies related to learning in general and learning in the mobile source sector that would be most relevant to the goals our report which include being a definitive, up-to-date, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically. In this section, we provide an overview of these 18 studies. The summaries are organized by topic, with respect to explanations of the variation in learning rates that was so clearly illustrated by the Dutton and Thomas (1984) histogram set out in Section 3.2, above. In addition, in their review of the literature on learning rates, Dutton and Thomas concluded that there is often more variation across organizations producing the same product than across organizations producing different products. Argote and Epple (1990) illustrated this variation by depicting learning curves from three truck plants that differed significantly in their rates of learning. Similarly, Chew, Bresnahan, and Clark (1990) found dramatic performance differences across plants in the same firm that produced the same or similar products. These findings underscore that learning is not automatic and is not determined by the product but rather depends on conditions at the organization that enable or hinder learning.[10] These conditions are now discussed.

The 18 articles examined four aspects of learning variation: sources of that variation (Section 4.1), the persistence and depreciation of organizational knowledge (Section 4.2), knowledge transfers and spillovers (Section 4.3), and the location of organizational knowledge (Section 4.4). The last set of articles provides qualitative descriptions of how learning curves can be applied (Section 4.5).

4.1. Sources of Learning Variation

4.1.1. Dutton & Thomas, 1984

Dutton and Thomas (1984) investigated whether future progress ratios could be predicted and how the rate of improvement could be managed by identifying which factors cause progress. The authors performed a secondary analysis of over 200 studies in a variety of industries such as electronics, machine tools, papermaking, and automobiles, drawn from 50 years of literature.[11]

The authors found that the rate of improvement was not fixed and could be influenced by managerial policy decisions. The authors identified four categories of factors related to progress: (1) technological progress in capital goods, (2) the Horndal-plant effect, (3) local system characteristics, and (4) scale effects. Technological progress in capital goods describes progress caused by cumulative investments and improvements in capital equipment. The Horndal-plant effect describes progress that results from direct learning (i.e., workers' improvement in performing a task); indirect labor learning (e.g., adaptation

[10] One of the peer reviewers agreed with the report's interpretation of the literature that heterogeneity in learning rates could be larger across organizations, even within an industry, than across industries and stated that this was an important point to highlight. See Appendix D for the full comments.

[11] The histogram presented in Section 3.2 features progress ratios from 108 studies, which were estimated in 22 field studies. Of the 200 studies, the histogram features only progress ratios from 108 studies that were quantitative, estimated organizational-level progress ratios, used unit cost or average cost as the outcome variable, and used cumulative volume as the independent variable.

of tooling and process changes made by staff or managers); and other cost-reducing measures such as scheduling, inventory management, quality control, and wage incentives. The local system characteristics category includes progress that results from an industry's or firm's operating system characteristics such as the degree of mechanization, the ratio of assembly to machining work, and the length of cycle times. Finally, the scale effects category includes progress that results from increases in the scale of operation.

While three of the categories of factors related to progress (i.e., technological change, labor learning, and organizational characteristics) continue to be regarded as important predictors of learning, the fourth category, economies of scale, is now seen as a variable that is distinct from learning and should be controlled for in empirical analyses. Economies of scale is the relationship between current inputs and current outputs while learning is the relationship between cumulative experience and current output.

4.1.2. Argote & Epple, 1990

Argote and Epple (1990) also identified potential factors that could affect organizational learning curves. Similar to Dutton and Thomas (1984), they performed a qualitative analysis of empirical studies focused on organizational learning curves. The authors identified factors that explain variation observed in organizational learning rates, especially organizational forgetting or knowledge depreciation and knowledge transfer.

Knowledge depreciation can be evident following an interruption in production due to factors such as strikes and input shortages when unit costs are higher than they were before the interruption (see Section 3.2). Knowledge acquired from learning can depreciate for reasons such as workers forgetting how to perform tasks, changes in the product or production processes making knowledge obsolete, workers being replaced by less experienced workers, records being lost, or routines being disrupted.

Additionally, employee turnover can influence rates of learning and forgetting—the extent to which it is able to do so depends on organizational characteristics. For instance, turnover is more likely to have an impact in organizations where jobs are not standardized and procedures do not exist for transmitting knowledge to new employees (Argote, 2013).

Knowledge transfer can also affect the learning rate (see Section 3.3). Knowledge transfer is the process through which one unit is affected by the experience of another. For example, knowledge transfer can occur across products, across shifts within a manufacturing facility, or across sister plants that are part of the same firm. A variety of mechanisms including communication, training, technology, routines, and personnel movement enable transfer. Organizations that are able to transfer knowledge effectively are more productive and have lower unit costs than their counterparts that are less adept at knowledge transfer. Through knowledge transfer, an organization leverages knowledge gained by one unit of the organization for the benefit of other units.

Finally, the authors point out that when estimating learning rates, one should control for factors alternative to learning that affect the learning rate. For example, not controlling for economies of scale can result in an overestimation of the learning rate (see also Balasubramanian & Lieberman, 2010).

4.1.3. Macher & Mowery, 2003

Macher and Mowery (2003) studied learning in the semiconductor industry related to the production of silicon wafers. The researchers examined how a manufacturer's performance (i.e., its learning rate) was influenced by human resource (HR) and organizational practices such as: teams for problem solving and intra-firm knowledge transfer, the use of information technology (IT), and workflow and production scheduling systems. Macher and Mowery conducted a quantitative regression analysis based on data from 36 wafer fabrication facilities from U.S., European, and Asian semiconductor firms.

The HR and organizational practices that improved performance included implementing problem-solving teams, policies that collocated production and key personnel, and the use of information handling automation and data analysis capabilities. The results showed that introducing HR and organizational practices initially negatively influenced performance, but the rate of improvement increased as production expanded. Interestingly, not all of the HR and organizational practices examined resulted in improved manufacturing performance. The authors concluded that those practices that did so improved performance by facilitating the organization's internal use of tacit knowledge. Nonaka, Toyama, and Bossier (2000) described tacit knowledge as "informal and hard-to-pin down know-how, crafts, and skills" and as "mental models, such as schemata, paradigms, perspectives, beliefs, and viewpoints" (p. 494).

Although the Macher and Mowery (2003) study was not conducted in the mobile source sector, its implications can still be useful. Results indicate that managers can actively implement strategies to facilitate learning.

4.1.4. Balasubramanian & Lieberman, 2010

Balasubramanian and Lieberman (2010) estimated the learning rate of over 100 industries in the manufacturing sector using the U.S. Census Bureau's Longitudinal Research Database and Compustat data from 1973 to 2000. By performing regression analyses using plant-level data, the authors also tested whether the learning rate was higher in industries with greater complexity (i.e., industries with higher capital, research and development (R&D), or advertising intensity) and whether the heterogeneity of firm performance was higher in industries with faster learning rates.

The results showed that organizations learned faster within industries that had greater capital-labor ratios as well as greater R&D and advertising intensity. These industries displayed productivity that was initially low but rose steeply with experience. Thus, Balasubramanian and Lieberman's (2010) article sheds light on several of the characteristics that explain variation in learning rates (see Dutton & Thomas, 1984).

Lieberman, one of our reviewers, concluded that our estimates are substantially in line with the learning rates Balasubramanian and Lieberman (2010) found for the mobile source sector (see Balasubramanin & Lieberman, 2011, for similar results using more fine-grained data). We should note that the learning rates in the Balasubramanian and Lieberman (2010) study, and the additional study by the same authors (Balasubramanian and Lieberman, 2011) were estimated using revenues less materials costs as the outcome variable, rather than unit cost, which is the focus of our analysis. Thus, we did not include their results to develop our summary effect. It is reassuring that approaches using different methods and data yield results consistent with ours.

4.1.5. Lapré & Nembhard, 2010

Lapré and Nembhard (2010) performed a secondary analysis of empirical studies related to organizational learning in manufacturing and service industries to determine why organizational learning rates vary. The authors distinguished between learning from experience and deliberate learning (i.e., "planned activities of managers and staff conducted with the explicit intent of acquiring, creating, and implementing new knowledge" (p. 41)), and found that both were important mechanisms for learning. Additionally, task and organizational characteristics were found to influence the learning rate.

Learning from Experience

Based on their review of the literature, the authors suggested that the impact of experience on an organization's learning rate can depend on whether the experience (1) was homogenous or diversified, (2) resulted in success or failure, and (3) occurred at the individual, team, or organizational level.

The authors did not find a consensus in the studies examined as to whether more homogeneous tasks, more diversified tasks, or tasks in the middle of the spectrum fostered a faster learning rate. Homogenous experience with the same specialized task gives individuals the opportunity to better understand a specific task and become more proficient at it; however, constantly repeating a task can lead to stagnation in the learning rate. Performing diverse tasks allows individuals to understand the bigger picture, but it can be costly to switch between tasks. Several of the studies showed that the best performance is observed when tasks are similar to each other. That is, performing similar tasks (moderate task heterogeneity) resulted in better performance than performing identical (low task heterogeneity) or different (high task heterogeneity) tasks.

The studies examined showed that although organizations learn from both successful and failed experience, they tend to learn more from failures. Once an organization experiences success, it is likely to reinforce past tactics and become more risk averse in an effort to preserve the status quo. Following a failure, an organization is more likely to critically review its past tactics and innovate new ways to improve its performance. The way an organization responds depends on four factors: (1) the nature of the success or failure, (2) the level of each experience and the presence of other experiences, (3) the aspiration level and (4) the context. The authors suggest there are four reasons for paying more attention to failures than success. First, outcomes with various causes are more complex to analyze than outcomes with a clear cause and therefore organizations tend to devote more resources to understanding and addressing them. Secondly, an organization is more likely to learn from either success or failure when the outcome surpasses a certain threshold. In addition, an organization will learn more from a success if it has had a related failure in the past. Thirdly, an organization is likely to learn from its own experiences if it succeeds but is more likely to learn from other organizations' experience if it fails. Finally, an organization is less likely to learn from failure if their competitors are also failing or if they have an historical investment in a strategy.

The studies examined by these authors suggest that experience results in learning at every level of the organization: individual, team, and overall organization. At the individual level, individuals develop skills and knowledge; at the team level, individuals learn how to coordinate and use each team member's skill the most efficiently; and at the organizational level, individuals learn from the knowledge accumulated by others. Reagans, Argote, and Brooks (2005) found that experience at the team and organizational level had a positive relationship with performance while individual experience had a U-shaped relationship with performance. At very low levels of experience, increases in experience hurt performance, while at high levels, increases in experience improved performance. At very low levels of experience, individuals might not apply the knowledge gained from previous experiences correctly, but this rectifies itself as the individuals accumulate more experience.

Deliberate Learning

With respect to deliberate learning, Lapré and Nembhard (2010) found that variations in the learning rate depend on: (1) the types of deliberate learning activities (DLAs) used and (2) contextual differences.

Types of DLAs include activities such as training, experiments, and quality management programs. Overall, it appears that learning rates are faster in organizations that use more types of DLAs than those that use fewer. Learning rates are also faster in organizations that use DLAs that contribute to their know-how and know-why.

In terms of contextual differences, a DLA's impact on the organizational learning rate depends on who is involved, their level of investment, where and when the DLA occurs, and why it has been pursued. Lapré and Nembhard (2010) found that a DLA impacts the learning rate the most when individuals at all levels of the organization (i.e., management, team leaders, and staff) actively support the chosen DLA, when the DLA is used in multiple locations within the organization, when there is enough time available to reflect on the knowledge gained from the DLA, and when the intention of the DLA is to improve quality rather than efficiency.

Task-based Learning

Task and organizational characteristics have also been found to affect the learning rate. Task characteristics focus on the knowledge required to complete a task with characteristics such as complexity, observability, and causal ambiguity. Tacitness was the task characteristic most focused on in this type of research. As explained above in Section 4.1.3, tacit knowledge is know-how that is difficult to articulate, while explicit knowledge is formalized and easily articulated. The authors found that the variation in the learning rates is related to the proportion of tacit-to-explicit knowledge in a task. Tasks with a higher proportion of tacit knowledge tend to have different learning rates due to the difficulty of learning tasks with little guidance, while tasks with higher proportions of explicit knowledge tend to have similar learning rates. In addition, knowledge gained from tasks that have complex, unproven, or causally ambiguous characteristics is also more difficult to transfer than knowledge from tasks that are less complex and better understood.

Organization Level Learning

Organizational characteristics include elements such as the internal structure (i.e., vertically structured organizations versus less interdependent organizations), organizational capacity, staffing, and expectations and incentives. The impact of internal structure on the learning rate depends on the business environment. In stable environments, vertically integrated organizations learn at a faster rate than less interdependent organizations; however, the opposite is true in volatile environments. Two types of organizational capacity have been found to increase learning rates. Organizations with more resource-based capacity (e.g., organizations that have more slack time) learn at faster rates because staff have more resources that assist in learning. Organizations with more absorptive capacity—the "ability to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990, p. 128)—are able to learn at faster rates because these organizations are better equipped to use new knowledge based on knowledge gained in their past experiences. Related to staffing, organizations with a higher percentage of temporary workers and more diverse teams tend to learn faster than those with a lower percentage of temporary workers and less diverse teams because these organizations can innovate better. Finally, organizations tend to base their incentive structures around their expectations of future performance. Because organizations have different expectations and subsequently have different incentive structures, workers engage in different types of learning activities (e.g., R&D); hence, different learning rates result.

4.1.6. Conclusion

Learning rates are not fixed and these five articles highlight several causes for variation in learning rates—several of which can be influenced by managerial policy decisions. Sources of variation include, but are not limited to, technological improvements, organizational practices, organizational characteristics, and the type of learning in which an organization engages.[12]

4.2. Knowledge Persistence and Depreciation

The conventional learning curve model shown in Equation 1 assumes that knowledge gained from learning by doing is cumulative and persists indefinitely over time. More recent research suggests that knowledge acquired from learning might not persist indefinitely in organizations (Argote et al., 1990; Darr et al., 1995). Instead, knowledge could depreciate due to factors such as turnover, interruptions in

[12] ICF also reviewed a study by Laitner and Stanstad (2004) who investigated the relationship between demand-side learning (i.e., "learning by using") and the cost of energy technologies. The authors found that demand-side learning could affect costs estimates and concluded that researchers should include learning on both the demand and supply side in their models to avoid biased results and forecasts.

production that lead to individuals forgetting how to perform tasks, disruptions in routines or changes in products and processes that render previous knowledge obsolete. Thus, while individual forgetting could contribute to knowledge depreciation in organizations, knowledge depreciation is caused by more factors than just individual forgetting.

The presence of knowledge depreciation does not negate the presence of learning curves. Just as individuals can continue to learn while they forget some material, organizations can also continue to learn while their stock of knowledge might depreciate.

Knowledge depreciation has typically been assessed by determining whether recent production experience is more important than earlier production experience in predicting current unit costs. The extent of knowledge depreciation is measured by estimating a parameter that determines the geometric weight past output receives in predicting current performance. If the parameter does not differ from one, there is no evidence of depreciation. A parameter less than one provides evidence of depreciation because it implies that past output receives less weight than recent output. That is, current performance is more driven by knowledge acquired recently than by knowledge acquired in the more distant past. The following five studies on knowledge depreciation were examined, each of which pertain to the mobile source sector.[13,14]

4.2.1. Epple, Argote, & Murphy, 1996

Epple et al. (1996) analyzed intra-plant knowledge transfer and knowledge depreciation in an automotive assembly plant that operated for 2 years with one-shift operation before adding an additional shift. This plant, a sister plant to the plant studied in Epple et al. (1991), used a different technology and introduced the second shift much later than the plant initially studied. In addition, more fine-grained data were available for this plant. Using 12 months of daily data related to the plant's one-shift operation and 15 months of data following their switch to two-shift operation, the authors investigated whether and how knowledge transferred between the first and second shift following the introduction of the second shift as well as between the two shifts during two-shift operation and whether knowledge acquired through learning by doing depreciated over time.

This study showed that knowledge depreciated in this mobile source plant. The estimated depreciation parameter, based on daily data was approximately ranged from .979 to .988, which implies that 0.6% - 5.5 % of the knowledge available at the beginning on one year would be available at the beginning of

[13] In order to estimate depreciation, researchers typically estimate a parameter that is the geometric weight that past output receives in predicting current production. This depreciation parameter represents the percentage of the knowledge stock acquired in one period that would carry over to the following period. Thus, the depreciation parameter can be thought of as providing an indicator of how much knowledge is retained from one period to the next. For example, a parameter estimated to be .98 would imply that 98% of the knowledge acquired in the previous period carried over to the current period. The period chosen for each study depended on the frequency of the data available (e.g., daily, weekly, or monthly). To facilitate comparisons of the estimated depreciation parameters between the studies, we converted all of the estimated depreciation parameters to an annual basis in the report. We describe the estimated depreciation parameters in the footnotes and in Column 3 of Table 3.

[14] A peer reviewer stated that Section 4.2 is a good characterization of studies about learning that have considered knowledge depreciation. See Appendix D for full comments.

the next. Of course, because the organization continued production, it generated new knowledge.[15] Rates of learning remained significant (see Table 1) when depreciation was taken into account.

4.2.2. Benkard, 2000

Benkard (2000) analyzed two groups of similar commercial aircraft models that consisted of four Lockheed L-1011 TriStar models and tested whether learning by doing, knowledge spillovers (see Section 4.3.2), or knowledge depreciation occurred during the production of the 250 units of aircraft between 1970 and 1984. Benkard conducted an empirical analysis by generalizing the traditional learning curve to allow for knowledge spillovers and knowledge depreciation.

Using monthly data, Benkard estimated annual depreciation parameters to be between .55 and .61, which implies that 55%–61% of the firm's experience that existed at the beginning of the year was available at the end of the year.[16] Benkard (2000) concluded that this was a relatively high rate of depreciation, which he attributed to characteristics of the aircraft industry which include low production rates, high labor turnover, and displacement rights which allow employees to request a higher position if one becomes available and can cause employee movement within the firm. Other industries in the mobile source sector that do not share these characteristics could experience less knowledge depreciation. Argote (2013) pointed out that Benkard's results showed that knowledge depreciation occurred despite incomplete knowledge transfers across products, which implies that knowledge depreciation was not solely caused by product changes that made previously gained knowledge obsolete.

4.2.3. Argote, 2013

Argote (2013) performed a secondary analysis of empirical studies on mobile source industries such as aircraft, ships, and automobiles as well as unrelated industries such as fast food franchises to determine whether organizational knowledge gained through learning by doing persisted or depreciated over time, the causes of knowledge depreciation, and whether turnover of key personnel affected organizational performance.

First, Argote (2013) reviewed the Lockheed L-1011 TriStar aircraft case study. Benkard (2000) analyzed the Lockheed data and found that knowledge depreciation occurred (see Section 4.3.2). Using monthly data, Benkard estimated the annual depreciation parameter to be between .55 and .61.[16] Argote also reviewed the empirical study conducted by Argote et al. (1990) regarding the production of Liberty ships during World War II, which found that knowledge depreciated rapidly with the annual depreciation

[15] The Epple et al. (1996) study estimated a daily depreciation parameter that ranged from 0.979 to 0.988. As calculated in Column 5 of Table 3, to convert the daily depreciation parameter to an annual basis, we raised the estimated parameter by 240 (i.e., the number of work days in a year). This finding indicates that, absent current production to replenish the knowledge stock, approximately 0.6% - 5.5% of the knowledge available at the beginning of one year would be available at the beginning of the next year.

[16] The Benkard (2000) study estimated a monthly depreciation parameter that ranged from 0.952 to 0.960. As calculated in Column 5 of Table 3, to convert the monthly depreciation parameter to an annual basis, we raised the estimated parameter by 12 (i.e., the number of months in a year). This result indicates that approximately 55% to 61% of the knowledge available at the beginning of one year would be available at the beginning of the next year.

parameter estimated to be between .01 and .14.[17] Argote then reviewed a study by Argote et al. (1997) conducted in an automobile assembly plant, which found less depreciation. Based on the monthly data, an annual depreciation parameter was estimated to be .56, which implied that 56% of the knowledge available at the beginning of one year would be available at the beginning of the next.[18] Further, there was evidence that organizational knowledge had both a permanent and a transitory component. The permanent component was attributed to procedural knowledge that is embedded in an organization's technologies or routines. For more discussion on the location of knowledge within an organization, see Section 3.4. Finally, Argote examined a study by Darr et al. (1995) on fast food franchises. Darr et al. estimated that only 0.001% to 0.01% of the knowledge stock available at the beginning of a year would remain at the end of the year, which is a very rapid rate of depreciation.[19] Along with the industry's high turnover rate, this depreciation rate could be due to its low level of technological sophistication.

Argote (2013) noted that debate has occurred in the literature about how much depreciation occurred in the production of Liberty ships during World War II. Argote et al. (1990) were the first to investigate knowledge depreciation and reported rapid knowledge depreciation, which suggested that between 1 and 14 % of the knowledge available at the beginning of a year would be available one year later. Thompson (2007) obtained additional data about Liberty ships from the National Archives and also found evidence that knowledge depreciated, albeit at a slower rate than Argote et al. (1990). His estimates suggested that between 49 % and 64 % of the knowledge available at the beginning of one year would be available at the beginning of the next.[20] Kim and Seo (2009) analyzed data from the shipyard that produced the largest number of Liberty ships. Using a different model than Argote et al., they found a similar estimate of the depreciation parameter, which implied that approximately 3% of the knowledge available at the start of one year would be available at the beginning of the next.[21] Thus, while all three studies of Liberty ship production found evidence of the depreciation, estimated amounts are sensitive to model specifications and variables included.

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[17] The Argote et al. (1990) study estimated a monthly depreciation parameter that ranged from 0.70 to 0.85. As calculated in Column 5 of Table 3, to convert the monthly depreciation parameter to an annual basis, we raised the estimated parameter by 12 (i.e., the number of months in a year). This result implies that approximately 1%-14% of the knowledge available at the beginning of a year would be available one year later.

[18] The Argote et al. (1997) study as cited in Argote (2013) estimated a weekly depreciation parameter of 0.989. As calculated in Column 5 of Table 3, to convert the weekly depreciation parameter to an annual basis, we raised the estimated parameter by 52 (i.e., the number of weeks in a year). This result implies that approximately 56% of the knowledge available at the beginning of a year would be retained one year later.

[19] The Darr et al. (1995) estimated a weekly depreciation parameter that ranged from 0.80 to 0.83. As calculated in Column 5 of Table 3, to convert the weekly depreciation parameter to an annual basis, we raised the estimated parameter by 52 (i.e., the number of weeks in a year). This results implies that only a negligible amount (approximately 0.01%) of knowledge available at the beginning of a year would be retained one year later.

[20] The Thompson (2007) study estimated a monthly depreciation parameter that ranged from 0.943 to 0.964. As calculated in Column 5 of Table 3, to convert the monthly depreciation parameter to an annual basis, we raised the estimated parameter by 12 (i.e., the number of months in a year). This result implies that approximately 49% to 64% of the knowledge available at the beginning of a year would be available one year later.

[21] The Kim and Seo (2009) study estimated a monthly depreciation parameter that ranged from 0.7379 to 0.7410. As calculated in Column 5 of Table 3, to convert the monthly depreciation parameter to an annual basis, we raised the estimated parameter by 12 (i.e., the number of months in a year). This result implies that approximately 3% of the knowledge available at the beginning of the year would be retained one year later.

4.2.4. Gopal, Goyal, Netessine, & Reindorp, 2013

Gopal, Goyal, Netessine, and Reindorp (2013) analyzed product launches in the North American automotive industry. Using the *Harbour Reports*, which contained production and launch data from 1999 to 2007 on 78 plants owned by former Daimler-Chrysler, Ford, GM, and Toyota, the authors evaluated how product launches affected a plant's productivity, and how any decreases in productivity resulting from the disruption caused by launches could be mitigated. The authors examined the 3 years prior to each launch and evaluated three types of experiences: (1) platform experience, the number of vehicles produced on the same platform as the launch product; (2) launch experience, the number of launches at the plant; and (3) firm experience, the number of launches within the firm. The authors tested whether the plant learned from these three types of experience and whether knowledge gained from these types of experience persisted over time.

Gopal et al. (2013) found that knowledge acquired from platform experience and knowledge acquired from past launch experience at the plant mitigated reductions in plant productivity during a new product launch. Further, knowledge acquired from platform experience tended to persist for 3 years while knowledge acquired through launch experience depreciated faster. The authors attributed the difference in persistence between platform and launch experience to the fact that while platform experience was consistently acquired over time, launches only occurred sporadically; hence, knowledge gained by launches was likely not reinforced or ingrained in routines.

4.2.5. Agrawal & Muthulingam, 2015

Agrawal and Muthulingam (2015) analyzed data from 295 vendors of a large car manufacturer in Asia with the aim of determining how knowledge depreciation affected the vendors' quality performance. The authors distinguished between two types of learning, learning by doing (autonomous learning) and quality improvement initiatives (induced learning). The authors analyzed data on 2,732 quality improvement initiatives implemented by the vendors between 2006 and 2009 using regression. To discern which factors influenced the rate of knowledge depreciation, the authors further examined the type of initiative and where the knowledge was located within an organization.

The authors found that knowledge depreciation affected quality gains obtained from learning by doing and quality improvement initiatives. Specifically, 16% and 13% of quality gains from learning by doing and quality improvement initiatives depreciated every year, respectively. These depreciation rates are lower than those observed in several other studies, which Agrawal and Muthulingam (2015) attributed to the low turnover rate during the study period and to the outcome variable used. Instead of unit costs, the authors used the defect rate, a measure of quality, which can be easier to document and track than cost measures. Additionally, quality problems are salient and are often addressed, which can contribute to a higher retention of knowledge.

The authors identified whether each of the 2,732 quality improvement initiatives primarily focused on (1) quality assurance, (2) process improvement, or (3) design quality. Quality gains from quality assurance initiatives did not depreciate; however, quality gains from process improvement initiatives depreciated by more than 14% per year (the authors did not analyze if quality gains from design quality initiatives depreciated, as the organizational learning estimates related to these initiatives were not significant). Agrawal and Muthulingam (2015) attributed these results to differences in how the initiatives addressed problems. Quality assurance initiatives often included solving the problem directly and making changes to test equipment. Hence, knowledge became embedded in technology. However, process improvement initiatives did not always solve the problem. The authors then evaluated whether the rate of depreciation depended on where the knowledge was embedded within the organization (see Section 4.4.3). They examined three locations: technology, routines, and organizational members (i.e., workers). The results showed that knowledge depreciated faster when it was embedded in individuals (26%), followed by routines (14%), and technology (9%).

4.2.6. Conclusion

Column 3 of Table 3 presents the depreciation parameter estimates found in 10 articles of the 18 articles that received a detailed review and the 15 articles related to the mobile source sector that received a cursory review. Column 5 presents the percentage of the knowledge stock held at the beginning of the year that would survive to the end of the year, if the knowledge stock were not replenished by production. It is important to note that most organizations continue production and thus replenish their knowledge stock. Estimated values of the depreciation parameter indicate how much knowledge is retained from one period to the next. Note that these estimates depend on specification of the model and the variables used.

Table 3. Summary of Depreciation Parameter Estimates

Author (Publication Date)	Industry	Depreciation Parameter Estimates	Data Frequency	Percent of Knowledge Remaining from One Year Ago
(1)	(2)	(3)	(4)	(5)
Agrawal & Muthulingam (2015)	Automobiles – Autonomous learning	.9852–.9866	Monthly	**84%–85%** (=$.9852^{12}$)–(=$.9866^{12}$)
	Automobiles – Induced Learning	.9752–.9994[a]	Monthly	**74%–99%** (=$.9752^{12}$)–(=$.9994^{12}$)
Argote, Beckman, Epple (1990)	Liberty ships	.70–.85	Monthly	**1%–14%** (=$.70^{12}$)–(=$.85^{12}$)
Argote, Epple, Rao, & Murphy (1997) as cited in Argote (2013)	Automobiles	.989	Weekly	**56%** (=$.989^{52}$)

Author (Publication Date)	Industry	Depreciation Parameter Estimates	Data Frequency	Percent of Knowledge Remaining from One Year Ago
Benkard (2000)	Aircraft (commercial)	.952–.960	Monthly	**55%–61%** (=$.952^{12}$)–(=$.960^{12}$)
Darr, Argote, & Epple (1995)	Fast food franchise	.80–.83	Weekly	**0.001%–0.01%** (=$.80^{52}$)–(=$.83^{52}$)
Epple, Argote, & Devadas (1991)	Trucks	.99[b]	Weekly	**59%** (=$.99^{52}$)
Epple, Argote, & Murphy (1996)	Automobiles	.979–.988	Daily	**0.6%-5.5%** (=$.979^{240}$)–(=$.988^{240}$)[c]
Gopal, Goyal, Netessine, & Reindorp (2013)	Trucks	N/A		
Kim & Seo (2009)	Liberty Ships	.7379–.7410	Monthly	**2.6%–2.7%** (=$.7379^{12}$)–(=$.7410^{12}$)
Levitt, List, & Syverson (2013)	Automobiles	.927–.965[d]	Weekly	**2%–16%** (=$.927^{52}$)–(=$.965^{52}$)
Thompson (2007)	Liberty Ships	.943–.964	Monthly	**49%–64%** (=$.943^{12}$)–(=$.964^{12}$)

Notes:

a. These values include depreciation parameters estimated from induced learning in general; learning from quality assurance, process improvement, and design quality initiatives; and learning from technology, routines, and operator solutions.
b. This depreciation parameter was not significantly different from 1—the case of no depreciation.
c. There are 20 work days in a month and 240 work days in a year.
d. The .927 value is the implied weekly depreciation parameter based on daily data which are compounded over a 5-day production week.

Current thinking on knowledge depreciation has focused on understanding the causes of depreciation (e.g., see the Agrawal & Muthulingam, 2015). Researchers acknowledge that the extent of depreciation can vary and they aim to understand the causes of the variation. On balance, knowledge appears to depreciate most rapidly in organizations where there is high turnover (see Darr et al., 1995), when rates of production are uneven or interrupted (see Benkard, 2000; Gopal et al., 2013), and when knowledge is embedded primarily in individuals rather than in routines or technology (see Argote, 2013; Agrawal & Muthulingam, 2015). Because organizations in mobile source industries tend to produce at a relatively even rate, embed a significant portion of the knowledge in technology and routines and do not experience turnover rates near the rates that Darr et al. reported in their study of fast food franchises, we do not expect knowledge depreciation to be large in mobile source industries.

It is important to note that learning continues to occur even though some of the knowledge acquired via learning by doing might depreciate. Just as individuals can forget some things while they continue to learn others, learning and "forgetting" (i.e., knowledge deprecation) can co-occur in organizations. Studies finding evidence of deprecation reviewed above continue to find evidence of learning.

4.3. Knowledge Transfer and Spillovers

Knowledge transfer is the process through which one organizational unit is affected by or learns from the experience of another unit. For example, a second shift introduced at a manufacturing plant might benefit from or learn from experience acquired on the first shift (see Epple et al., 1991) or the manufacture of a new model of a product might benefit from experience acquired producing the initial model (Benkard, 2000). Knowledge transfer has been studied within and between plants. The concept of knowledge spillover is identical to the concept of knowledge transfer. Economists tend to use the term "spillover" while management researchers generally use the term "transfer." Knowing whether intra-plant transfers occur is useful in identifying sources of learning within firms. Furthermore, analyzing intra-plant transfers allows researchers to determine where knowledge is embedded within organizations. For examples of studies doing so, refer to Section 3.4. Three studies focused on knowledge transfer in mobile source industries.[22,23] (Note, that these studies do not address all of the components of knowledge transfer (e.g., inter-firm spillover) because distinguishing the separate components of learning is not an objective of this report.)

4.3.1. Epple, Argote, & Devadas, 1991

Epple et al. (1991) analyzed intra-plant knowledge transfer between shifts in a North American truck plant. The plant operated with one shift for 19 weeks and then added a second shift. Specifically, the authors assessed the knowledge transfer that occurred between the first and second shift when the second shift was introduced as well as the ongoing transfer between the first (day) and second (night) shifts during two-shift operation. Eighty weeks of data were analyzed from the period after the second shift was introduced. The authors extended the conventional learning curve model by allowing for knowledge depreciation, a changing learning rate, and intra-plant knowledge transfer.

Significant but incomplete transfer of knowledge occurred from the first to the second shift when it was introduced. Results indicate that 69% of the knowledge acquired during the period of operating with one shift transferred to the period of operating with two shifts. Once both shifts were operating, about half (56%) of knowledge acquired on one shift transferred to the other shift. The authors compared their

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[22] ICF also reviewed a study by Thornton and Thompson (2001) who analyzed knowledge spillovers across shipyards in the production of Liberty ships produced during World War II. The authors found that knowledge spillovers had a significant impact on increasing productivity.

[23] One of the peer reviewers commented that Section 4.3 is effective in describing research findings relating to knowledge transfer across organizational units (e.g., additional shifts and new models) within a given firm. See Appendix D for full comments.

results to those of Argote et al. (1990) who investigated knowledge transfers between shipyards producing ships during World War II. Similar to the results of Epple et al. about the introduction of a second shift, Argote et al. found that when shipyards began production, they benefited from the experience of shipyards with earlier start dates. In contrast to the Epple et al. results on cross-shift transfer, Argote et al. did not find evidence of ongoing knowledge transfer between shipyards once they were in operation.

4.3.2. Benkard, 2000

Benkard (2000) analyzed the extent of knowledge spillover or transfer during the production of two groups of similar commercial airline models (specifically, four Lockheed L-1011 TriStar models) between 1970 and 1984. Benkard's empirical analysis generalized the traditional learning curve by allowing for organizational forgetting and knowledge spillover. His analysis took into account that experience gained from working on one group of airline models might differ from experience gained from working on the second group.

Benkard found that when production was switched to a new model, approximately 70% of the knowledge transferred. Hence, there was considerable but incomplete knowledge transfer to a new model. The author interpreted 70% as being relatively low given that the two groups of models were similar and produced at the same plant. The results showing incomplete knowledge transfers led Benkard to conclude that (1) introducing a new model can cause production costs to increase and (2) producing multiple models simultaneously can cause production costs to be higher than if only one model were produced.

Caution should be used when comparing the amount of knowledge transfer in the aerospace industry to other mobile source industries due to the nature of commercial aircraft production, which involves labor-intensive production processes, low annual output, high entry costs and imperfect competition. Other industries that do not share these characteristics might exhibit different patterns related to the extent of knowledge spillover.

4.3.3. Levitt, List, & Syverson, 2013

Levitt et al. (2013) analyzed learning and knowledge spillovers at an automobile assembly plant. The authors used production data, absenteeism records, and warranty claims to conduct quantitative analyses to estimate learning's impact on defect rates. Similar to Epple et al. (1991), the authors analyzed knowledge transfer across shifts in an automotive plant. Similar to Benkard (2000), Levitt et al. analyzed knowledge transfer across different product models. Unlike Epple et al. and Benkard, Levitt et al. analyzed quality improvements (i.e., reductions in the average defect rate) rather than unit costs as their outcome variable.

While analyzing knowledge transfers between the first and second shifts, Levitt et al. (2013) found evidence of knowledge transfer: from the outset, the defect rates in the second shift were lower than they were during the first shift. On average, the defect rates in the second shift were 5% to 10% lower than those in the first shift. Furthermore, defect rates in the first shift increased during the second shift's ramp-up period.

The authors also tested for knowledge transfer between three models. Defects in Model 1 increased during the ramp-up period of Models 2 and 3; however, defects in Model 2 were not significantly related to the ramp-up period of Model 3. The authors concluded that because Model 3 was a specialized version of Model 1, more resources were taken away from Model 1's production for problem solving during Model 3's ramp-up period. The results of Levitt et al. (2013) on cross product transfer are consistent with Benkard's (2000), who found that the addition of a new model can negatively impact the production of existing models.

Finally, Levitt et al. (2013) found spillovers between cars produced sequentially on an assembly line. A defect on a car significantly increased the likelihood of defects on the next 15 cars, although the magnitude of the defects decreased the further the cars are from each other.

4.3.4. Conclusion

These three studies found evidence of knowledge transfers between shifts and product models. Epple et al. (1991) found that 69% of the knowledge acquired during the period of operating with one shift at a truck plant transferred to the period of operating with two shifts. Once both shifts were operating, 56% of knowledge acquired on one shift transferred to the other shift. Benkard (2000) found that approximately 70% of knowledge transferred when production of a commercial aircraft was switched to a new model. Levitt et al. (2013) found evidence of positive knowledge transfers at an automobile plant between the first and second shifts and evidence of negative transfer when new models were introduced (i.e., the addition of two new models harmed production of the initial model).

4.4. Location of Organizational Knowledge

Understanding the learning process requires, along with topics discussed in other sections, a comprehension of where knowledge is embedded in organizations. Knowledge can be embedded in individual employees, in tools and physical capital, or in routines and procedures for accomplishing tasks. Knowing where knowledge is embedded can assist managers in choosing a production strategy that would increase production rates and thereby decrease per unit costs. There is agreement across the following three articles, which found that organizational knowledge resides in multiple locations. In addition, Agrawal and Muthulingam (2015) found that organizational knowledge is not equally retained within each location.[24] Finally, the fourth article by Bahk and Gort (1993) found that the conventional learning curve could be expanded upon by decomposing learning by doing into different types of learning.

[24] The study conducted by Epple et al. (1996) also analyzes the location of knowledge (see Section 4.2.1). The study is not summarized here, but its results are consistent with the three articles presented in this section.

4.4.1. Epple, Argote, & Devadas, 1991

Using 2 years of weekly data from a North American truck plant, Epple et al. (1991) analyzed what proportion of knowledge acquired during 19 weeks of one-shift operation was carried forward as the plant transitioned to two-shift operation as well as what proportion of knowledge was transferred between the day and night shifts during two-shift operation. Workers on both shifts used the same tooling and physical capital. Workers on the second shift were new to the organization, having recently been hired to work on the second shift.

The results indicated considerable but incomplete knowledge transfers between one- and two-shift operations as well as between day and night shifts (see Section 4.3.1). Because the same equipment and physical facilities were used on both shifts, the authors attributed a significant amount of the knowledge transfer to knowledge being embedded in the organization's technology, which includes plant layout, equipment, and computer software. That is, as the first shift gained experience in production it made improvements in the tooling and technology. Because the second shift used the same technology as the first shift, it benefited from knowledge embedded in the technology by the first shift.

4.4.2. Levitt, List, & Syverson, 2013

Similar to Epple et al. (1991), Levitt et al. (2013) aimed to discern the location of organizational knowledge by analyzing knowledge transfer between shifts at an automotive assembly plant. Using one year of production, absenteeism, and warranty claims data from an automotive assembly plant that transitioned from one- to two-shift production, the authors evaluated the relationship between production experience and defect rates and between absenteeism and defect rates. While the Epple et al. study analyzed knowledge transfers at a plant producing one vehicle model, Levitt et al. examined transfers at a plant producing three models (see Section 4.3.3).

Similar to the results of Epple et al. (1991), Levitt et al.'s (2013) results indicate that a significant amount of organizational knowledge was embedded in the broader organization or physical capital, rather than in the workers. The following findings led them to this conclusion: (1) experience gained during first-shift operation appeared to be fully incorporated in the second-shift operation, despite the fact that new workers were employed on the second shift;[25] (2) workers were not able to fully transfer their production knowledge from one model to new models; (3) the distribution of defects among stations was similar between day and night shifts, although the workers were different; and (4) although absenteeism varied significantly over the analysis period, the defect rate only experienced minor changes.

We should note that due to the nature of their data set, Levitt et al. (2013) focused on how learning affects defect rates, unlike Epple et al.'s (1991) study, which focused on how learning affects unit costs.

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[25] Epple et al. (1996) found a similar result while studying knowledge transfers at an automotive assembly plant and drew a similar conclusion that knowledge appears to be embodied in the broader organization rather than the human capital of workers.

Analyzing learning related to quality measures could have implications for learning related to unit costs. Correcting defects identified at the plant typically causes costs to increase.

4.4.3. Agrawal & Muthulingam, 2015

Agrawal and Muthulingam (2015) evaluated how organizational learning and knowledge depreciation affect the quality performance of car manufacturer vendors. The authors focus on quality improvement initiatives, which they refer to as "induced learning." The authors used data from a large automotive manufacturer in Asia, which included 2,732 quality improvements initiatives implemented by the car manufacturer's 295 vendors between 2006 and 2009. The authors categorized the initiatives as focused primarily on technology (e.g., new equipment), routines, or operators (e.g., training). The authors conducted an empirical analysis, using regression to analyze the relationship between the stock of induced knowledge related to quality improvement projects with technology, routines, or operator solutions and the defect rate.

The authors found that the rate of knowledge depreciation depends on where knowledge is located. Knowledge embedded in operators depreciates faster than knowledge embedded in organizational routines or technology. Annually, 9%, 14%, and 26% of knowledge embedded in technology, organizational routines, and operators depreciated, respectively.

Similar to Levitt et al. (2013), this study analyzes the defect rate instead of unit costs. This study differs from Epple et al. (1991) and Levitt et al. because it differentiates between learning by doing and induced learning.

4.4.4. Bahk & Gort, 1993

Bahk and Gort (1993) analyzed the magnitude of firm-specific learning by doing and aimed to decompose learning by doing into three elements: organizational learning, capital learning, and labor learning. The authors also investigated the length of time over which learning accumulated. The authors evaluated new plants in multiple industries using a 15- and 41-industry pool of samples from U.S. Census Bureau data that spanned from 1973 to 1986. The authors aimed to distinguish the relationship between learning by doing and the outcome variable (i.e., shipments or value added) from the relationship between labor accumulation, human capital, physical capital, and embodied technical change (i.e., change that is reflected in labor or capital inputs) and the outcome variable.

Bahk and Gort (1993) found that learning by doing significantly increased output. The authors concluded that industry-wide learning was related to embodied technical change and physical capital. The authors also found that the rate at which learning by doing declined varied by the type of learning. Organizational learning continued for 10 years following the birth of a plant while capital learning continued for only 5 to 6 years following the birth. Labor learning could not be measured with their data.

The authors used shipments and value added as outcome variables in this analysis. Shipments may not be a good measure of productivity because firms often store output in inventory prior to shipping it. The authors acknowledge that value added was a relatively weak outcome variable because it contained measurement errors. Both shipments and value added appear to be measured in dollar value (see page 580), which raises an additional concern. Such measures would embody price and therefore are likely to confound supply-side learning with demand-side changes that might not be related to learning.

4.4.5. Conclusion

These four articles have found evidence that organizational knowledge resides in multiple locations. Epple et al. (1991) and Levitt et al. (2013) found that a significant amount of organizational knowledge was embedded in the broader organization or physical capital such as its technology. Agrawal and Muthulingam (2015) found that knowledge embedded in operators depreciates faster than knowledge embedded in organizational routines or technology. Bahk and Gort (1993) found that embodied technical change and physical capital drove industry-wide learning and that organizational learning continued longer than capital learning.

4.5. Application of the Learning Curve

The final five studies reviewed for this report provide examples of how learning rates are being used to evaluate learning in mobile source and other industries. Bernstein (1988) described how learning was used in an organization's automotive plant to reduce costs by reducing absenteeism and turnover. Studies such as Rubin, Taylor, Yeh, and Hounshell (2004), Shinoda et al. (2009), and Nykvist and Nilsson (2015) examined the learning rate with the aim of forecasting the future cost of technologies to determine when the technology would be cheap enough to be competitive on the market. Other studies such as Rubin et al. (2004) and Lee, Veloso, Hounshell, and Rubin (2010) analyzed how learning is affected by government regulations.

4.5.1. Bernstein, 1988

Bernstein (1988) performed a case study on Volvo's use of long-term organizational development programs in its Swedish automotive plants. In the 1960s and 1970s, during a "Spontaneous Trial Period," Volvo allowed trial plants to add to their socio-technical knowledge stock by experimenting with various solutions to issues such as high absenteeism and turnover. During the "Socio-Technical Strategy Period," using feedback from employees at the trial plants, Volvo implemented practices that were tailored to specific problems, such as giving newly created teams supervisory and quality control responsibilities, providing monetary incentives for staff to learn new skills, and creating workplaces with low supervisor-to-worker ratios. In the 1970s and 1980s, Volvo also created organizational development programs that stressed communication and worker involvement.

Volvo experienced success that was evident in the reduction of their high absenteeism and turnover rates over the period of the study. According to Bernstein (1988), the organization's trial-and-error method helped the organization to move down the learning as learning occurred at all levels within the organization. Volvo found solutions to issues with their labor force and their focus on communication helped them spread the knowledge gained between plants. The SME pointed out that these socio-technical changes, however, were dismantled in the 1990s (see Adler & Cole, 1993; Berggren, 1994).

4.5.2. Rubin, Taylor, Yeh, & Hounshell, 2004

Rubin et al. (2004) described the common practice of using exogenous or arbitrary rates of change in cost or efficiency over time in energy economic models that study global climate change and carbon management options. The authors aimed to produce more accurate estimates that reflected how costs change in response to government actions or policies. The authors focused on two environmental technologies used in electric power plants. Data from 5 years were used to estimate the learning rate of flue gas desulfurization (FGD) systems (i.e., 1976, 1980, 1982, 1990, and 1995), which control sulfur dioxide (SO_2) emissions, and selective catalytic reduction (SCR) systems (i.e., 1983, 1989, 1993, 1995, and 1996), which control mono-nitrogen oxide (NO_x) emissions.

The authors found that FGD systems exhibited a progress ratio of 89%, which implies that for each doubling of installed FGD capacity, capital cost would decrease by 11%. The progress ratio and learning rate for SCR systems was similar with a progress ratio of 88% and a learning rate of 12%.

Rubin et al. (2004) did not provide much information about the source of the data, which makes it difficult to replicate the analysis or to determine its reliability. Additionally, the data only consisted of five data points spanning from 1976 to 1995 for FGD systems and from 1983 to 1996 for SCR systems. Yet, most of the capacity was added after 1980 and 1989 for FGD and SCR systems, respectively. If the model excluded the outliers and the regressions were repeated using only the four data points after 1980 and 1989 for FGD and SCR systems, respectively, the learning curve would have indicated learning occurred at a faster rate.

4.5.3. Shinoda, Tanaka, Akisawa, & Kashiwagi, 2009

Shinoda et al. (2009) used a model that incorporated learning to predict scenarios of how widely used plug-in hybrid electric vehicles (PHEVs) would be over the period between 2010 and 2030. The authors aimed to find a scenario that minimized the total cost in the passenger car sector and power supply sector. PHEVs are another example of technologies that have benefits (i.e., they reduce carbon dioxide (CO_2) emissions), but the battery costs are currently too expensive to be competitive.

The authors found that for PHEVs to be competitive in the market by 2030, the battery cost must drop to approximately 132,000¥ by 2015 if the batteries were not replaced and approximately 125,000¥ if they were. The authors estimated that if the price dropped to 100,000¥/kWh by 2010, PHEVs could comprise over 60% of the new vehicles bought in Japan in 2030.

Unlike other articles examined, Shinoda et al. (2009) used price as the outcome variable in their learning estimates instead of unit costs. Price is affected by firm strategy and market conditions. For example, a firm might price its product below unit costs to attempt to gain market share. Thus, price would not be a good indicator of unit costs.

4.5.4. Lee, Veloso, Hounshell, & Rubin, 2010

Lee et al.'s (2010) study focused on whether learning occurred during the technological development caused by "technology-forcing regulations" in the automotive industry. Technology-forcing regulations set performance standards, which require organizations to develop or improve technology to meet them. The authors combined data from 1970 to 1998 from the U.S. Patent and Trademark Office, technical papers published by the Society of Automotive Engineers, and cost data on automobile emissions control devices from the EPA and California Air Resource Board (CARB) with qualitative sources such as interviews with experts.

By analyzing trends in patents and papers published, the authors concluded that the level of innovation from automakers and suppliers increased when technology-forcing regulations went into effect. During periods of stricter regulations, which the authors claimed caused uncertainty in the industry[26], they found that automakers dominated architectural innovation, while suppliers dominated component innovation. However, despite the innovation, Lee et al. (2010) did not find that learning occurred after 1984. The authors suggested that any cost reductions due to learning could have been cancelled out by increases in the cost of precious metal catalysts. Cost of precious metals fluctuated and increased radically during that period. The authors then examined non-catalyst components, which were not affected by the cost of precious metals, and estimated that during 1984 and 1990, learning occurred with a progress ratio of 93%. However, much of the innovation during that period involved catalyst improvements together with fuel regulations. The seven data points which were used by these authors make their finding a rough estimate at best as described by the authors.

A further note is that while technology-forcing regulations were used in the 1970s and 1980s, by the mid-1990s, EPA and CARB started working with automobile manufacturers in developing standards. This led to even tighter standards, which the industry could accomplish and provided environmental benefits for the regulatory agencies. Furthermore, there is a concern that the number of patents and papers would measure the relationship between cost and technological change rather than learning.

4.5.5. Nykvist & Nilsson, 2015

Nykvist and Nilsson (2015) estimated the current costs of Li-ion battery packs for battery electric vehicles (BEVs) and forecasted future costs to determine if the battery packs would be cheap enough for BEVs to become competitive with internal combustion vehicles. The authors analyzed over 80 cost estimates from peer-reviewed articles; grey literature (i.e., work that is not formally published); estimates from agencies, consultants, industry analysts, and leading BEV manufacturers; and news reports from 2007 to 2014.

[26] Both CARB and EPA do Regulatory Impact Analyses that provide costs and potential technologies to use to meet any proposed standards. Uncertainty only lies in calibration of engine systems to work with the new technologies.

The authors estimated that the current learning rate was 9% for the overall industry and 6% for the market-leading manufacturers by regressing cost data on cumulative output.[27] From 2007 to 2014, industry-wide average costs declined by 14% annually, while average costs for the market leaders declined by 8% annually. The authors expected BEV battery costs to continue declining 8% annually in the future. At this rate, the battery pack would not be cheap enough for BEVs to be competitive by 2030. However, Nykvist and Nilsson (2015) noted that the forecasted 8% rate was made under the assumption that there would be no breakthroughs in technology for similar batteries and that with the public's continued support of BEVs, manufacturers would continue to produce the batteries and take advantage of economies of scale. [28]

Nykvist and Nilsson (2015) listed several areas of concern with their quantitative analysis that surrounded their results with uncertainty. These issues included variance in costs, variance in the types of batteries analyzed, incentives by industry to overestimate costs or subsidize production, and the sparse availability of data.

4.5.6. Conclusion

These five studies provide examples for how learning curve research is being applied to real-world issues in the mobile source sector. Applications range from observing companies, such as Volvo, move along the learning curve to predicting the costs of future technologies.

[27] One commenter on this report noted that the Nykvist and Nilsson learning rate of 9% would result in a 91% progress ratio, and suggested that it would be informative to consider possible sources of this large discrepancy in learning rates between Li-ion battery manufacturing and transportation equipment final assembly. See Appendix D with respect to the response to this comment.

[28] In EPA's Final Rulemaking for 2017–2025 Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards, EPA applied a learning curve to battery pack development. Like Nykvist and Nilsson (2015), EPA's models projected that the cost of producing battery packs would experience a sharp decline in the initial years of development (i.e., the research phase) and would later experience a slower decline along the flat portion of the learning curve.

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5. Responses to Peer Reviewer Comments Related to the Analysis

This report has undergone peer review. While the peer reviewers found the literature review of the 18 selected studies in Section 4 to be comprehensive, they suggested 3 additional articles for consideration. We added two of these to our reviews; the third was unrelated to our work. The peer reviewers also raised a number of questions, the most significant of which are discussed here with regard to the shape of the learning function, supply- vs. demand-side effects; learning effects and economies of scale; and net learning effects. A summary of all of the peer reviewers' comments and our responses can be found in Appendix D.

First, a peer reviewer questioned whether the logarithmic learning curve should be estimated with an initially "steep" portion followed by a "flat" portion or whether it should be estimated with a constant slope over time (see Comment #19 under "Literature Review – General" in Appendix D). In response to this comment, we reviewed our five selected articles and found that only one of the articles included a model with a quadratic term, which allows one to investigate whether the rate of learning slows down in logarithmic form. Epple, Argote, and Devadas (1991) found that the quadratic term was significant, which suggested that there was a diminution in the learning rate in their empirical context. Because only one of the five studies investigated whether the rate of learning slowed down, we did not see a basis for departing from the standard model used in the literature (see Equation 1). It is important to note that the power function shown in Equation 1 has the property that it is steeper in the earlier part of the curve than in the later part. Although the rate of learning is constrained to be the same in Equation 1 for different levels of cumulative output, it takes longer for cumulative output to double later (e.g., going from 100, 000 to 200,000 units) than earlier (e.g., going from 1,000 to 2,000 units) in the production program. Hence the learning curve is flatter later in the production program (see Figure 1).

Second, another peer reviewer noted that studies using price as a variable are likely to confound supply-side learning effects with demand-side changes that could be unrelated to the learning process. The peer reviewer pointed out that this concern applies to using shipments as an outcome variable because shipments are reported in real dollar values, thereby raising the supply-versus-demand conundrum. The reviewer argues that this concern was not always made clear in the report (see Comment #21 under "Literature Review – General" in Appendix D). We agree with the peer reviewer and we added this issue as an additional concern when using shipments as an outcome variable. We did not use studies with shipments as an outcome variable when estimating our recommended value.

Third, a peer reviewer commented that there is a distinction between learning curves and economies of scale and that the report provides no guidance on how to perform a cost analysis forecast that incorporates learning and economies of scale as separate elements. The reviewer argued that several studies (e.g., Lieberman, 1984) have shown that when controls for economies of scale are omitted from the analysis, the estimated progress ratio includes the effects of both learning and scale economies. We re-examined the studies and found that adding a separate parameter for economies of scale normally improves the statistical fit but, as the reviewer points out, the improvement is seldom dramatic, and most studies have found scale economies to be less important than the learning effect. Moreover, if the data sample is small, collinearity between the learning and scale parameters can reduce the accuracy with which each is estimated. The reviewer further noted that an implication is that if the analyst or policy maker is able to apply only a single cost driver for forecasting purposes, application of a learning curve or progress ratio to forecasted cumulative output may provide the best projection of future costs (see Comment #26 under "Literature Review – Sources of Learning Variation (Section 4.1)" in Appendix D).

In response to the comment, there are two ways to investigate the effect of scale economies and learning. One way is to include both current output (i.e., scale) and cumulative output up to the previous period (i.e., not including the current period learning) as predictors (e.g., see Darr, Argote & Epple, 1995). Another way is to estimate production functions with measures of labor and capital and investigate if there are economies of scale as indicated by coefficients greater than one. Due to the difficulty of getting fine-grained measures, especially of capital, few researchers are able to follow the latter approach. Further, as the reviewer notes, collinearity between the learning and scale effects can reduce the accuracy with which each is estimated. As the reviewer notes, most studies that include scale economies have found scale economies to be less important than learning (i.e., cumulative output). Further, as the reviewer notes, "One implication is that if the analyst or policy maker is able to apply only a single cost driver for forecasting purposes, application of a learning curve or progress ratio to forecasted cumulative output may provide the best projection of future costs."

Fourth, a peer reviewer commented that the progress ratio estimated from the five selected studies are not based upon the total cost of production and that the report should be clear about the need to consider cost reduction of the component parts as well as the learning curve in the final assembly plant. We point out that studies that have had measures of other costs find that they also follow a learning curve. For example, Darr, Argote & Epple (1995) found that total costs, which included material as well as labor, followed a learning curve. Similarly, Balasubramanian and Lieberman (2010) included material costs in their measure, which exhibited a learning effect.

Finally, a peer reviewer commented that one objective of this report is to identify the expected pace at which mobile source manufacturing productivity should improve with production experience. Therefore, we should be attempting to identify a net effect of learning and depreciation rather than the gross learning rate. While it may not be possible to derive a bottom-line net learning rate parameter that is as comparable and applicable as the gross parameter the study reports now, the reviewer argued that we should discuss the net-versus-gross distinction and how it might matter when applying the findings of the report to practical settings (see Comment #30 under "Literature Review – Knowledge Persistence and Depreciation (Section 4.2)" in Appendix D).

We appreciate the reviewer's comment about the net-versus-gross distinction. The investigation of depreciation is a newer area than the investigation of learning. We identified ten studies that estimated the rate of depreciation (see Table 3). If one eliminates the studies analyzing data on the production of Liberty ships during World War II, the number drops to seven. Estimating the rate of depreciation requires considerable data in order to disentangle the rate of depreciation from the rate of learning and other effects such as calendar time, with which it is likely to be correlated. For example, Levitt, List and Syverson (2013) found evidence of knowledge depreciation but also concluded (see page 657): "explicitly modeling the forgetting process does not substantially improve the ability of the power law specification to fit the data, particularly relative to simply controlling for a time trend."

As we noted in our report and the reviewer ratified, mobile source manufacturing has several properties (e.g., relatively even rates of production, learning embedded in routines and technologies, modest amounts of worker turnover) that are likely to lead to low levels of knowledge depreciation. Comparing rates of depreciation found in three different empirical contexts, Argote (2013, p. 80) concluded that the rate of depreciation found in a truck assembly plant was less than the rate of depreciation found in World War II shipyards, and both were less than the rate of deprecation found in fast food franchises. This pattern can be seen in Table 3: The fastest depreciation (and correspondingly the least retention) was found in the study of fast food franchises (Darr, Argote & Epple, 1995), followed by studies of World War II shipyards (Argote, Beckman & Epple, 1990; Kim & Seo, 2009).

As noted previously, the rate of depreciation is not likely to be high in modern mobile source industries. And it can be difficult to disentangle the effect of depreciation from other effects, such as time, with which it is likely to be correlated. Further, our goal in the report was not to provide estimates of the various subcomponents of learning but rather to provide an overall summary effect. For these reasons, our summary learning effect is based on cumulative output without considering depreciation.

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Appendix A. Method of Estimating Impacts of Learning

The goals of this report are (1) to be a definitive, up-to-date, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically; (2) to develop a single compendium study on industrial learning in the mobile source sector that could be considered for use in future OTAQ costs analyses; and (3) to develop a summary effect of learning based on cumulative output in mobile source industries

This section begins with a discussion of how learning rates and progress ratios are calculated. The section then develops two methods for estimating the impacts of learning and discusses when one method would be preferable to the other. These approaches could be used by OTAQ in future cost analyses. To demonstrate the approaches, we use the summary effect of learning described in Section 3.4 in a hypothetical example. Because the methods rely on Equations 1–4 in Section 3.1 and 3.2, those sections are repeated here for ease of referral.

Calculating Learning Rates and Progress Ratios

The conventional form of a learning curve is a power function:

$$y_t = a\, x_{t-1}^{b} \qquad \text{(Eq. 1)}$$

Where:

x_t	=	Cumulative number of units produced by an organization (i.e., experience gained) by date t
y_t	=	Costs required to produce an additional unit at date t
a	=	Costs required to produce the first unit
b	=	Parameter that measures the rate unit costs change as cumulative output increases. If learning occurs, b<0.
t	=	Time subscript

While learning curves are typically expressed as the relationship between costs per unit and production volume, other dependent measures have been used including the amount of time it takes to produce a unit of output, defects per unit, or accidents per unit. The particular dependent measure used depends on the researcher’s purpose. Our focus in this report is on unit costs.

Equation 1 can be rewritten in logarithmic form:

$$\ln(y_t) = a + b\ln(x_t) \qquad \text{(Eq. 2)}$$

In actual organizational settings, learning is expected to be more complicated than the simple form expressed in Equation 1, and costs are affected by more than just production volume. Indeed, researchers have examined myriad other factors that can also affect learning, such as organizational forgetting and knowledge transfer or spillover (i.e., learning from the experience of other organizational units). Equation 1 can be generalized to investigate these issues.

Organizations often characterize their learning rates in terms of a progress ratio, p, which describes how the outcome variable changes when cumulative output doubles. For example, the interpretation of an 80% progress ratio is that for every doubling of cumulative output, the outcome variable (e.g., costs per unit in Equation 1) declines to 80% of its previous value. An 80% progress ratio means that costs decline by 20%. Thus, lower progress ratios imply faster learning because costs are declining at a faster rate.

A progress ratio, p, can be computed from the learning rate, b, as follows:

y_1 = Unit cost after producing x_1 units

y_2 = Unit cost after producing $2x_1$

$y_1 = ax_1^b$

$y_2 = a(2x_1)^b$

$$p = \frac{y_2}{y_1} = 2^b \qquad \text{(Eq. 3)}$$

Conversely, the learning rate, b, can be computed from the progress ratio, p:

$\ln(p) = b\ln(2)$

$$b = \frac{\ln(p)}{\ln(2)} \qquad \text{(Eq. 4)}$$

Method for Estimating Future Costs Incorporating Learning

In order to estimate future costs based on learning, we extend the framework in Equation 1 to accommodate multiple organizations as follows. Let:

$x_{i,t}$	=	Cumulative number of units produced by organization i through date t.
N	=	Number of organizations producing the product
$X_t = \sum_i^N x_{i,t}$	=	Cumulative number of units produced in the industry by date t

A conservative approach for estimation purposes is to assume symmetric production across organizations so that production by each organization by date t is the same across organizations:

$$x_{i,t} = x_t = \frac{X_t}{N} \qquad \text{(Eq. 5)}$$

This approach is conservative in two respects. First, it assumes no transfer of knowledge across organizations. If transfer across organizations occurs, costs would decline more rapidly. Second, the approach assumes symmetry. Industry costs would decline more rapidly if production were asymmetrically distributed across organizations, absent diseconomies of scale, than if symmetrically distributed. This approach is conservative in the sense that it would underestimate the amount of learning if knowledge transfer occurs or if production were distributed unevenly across organizations. With production per organization, x_t, defined as in Equation 5, cost for production of the next unit as given by Equation 1 applies both at organizational and industry levels.

Two methods are described for estimating future costs from the above equations. Here is the notation used for both methods:

y_{t+1}	=	Costs required to produce a unit at time t+1
y_t	=	Costs required to produce a unit at time t
a	=	Costs required to produce the first unit
q_{t+1}	=	Number of units forecast to be produced in year (t+1)
x_t	=	Cumulative number of units produced through period t
x_{t+1}	=	Cumulative number of units produced through period t+1 = $x_t + q_{t+1}$
b	=	A parameter measuring rate unit costs change as cumulative output increases – the learning rate
X_t	=	Cumulative number of units produced by industry
N	=	Number of organizations producing the product

Both approaches require information about the learning rate, cumulative output (x_t), and forecasts of the number of units to be produced by the industry in the coming period (q_{t+1}) as well as the number of organizations involved in production.

The learning rate (b) can be calculated from the progress ratio (p) according to Equation 4. Based on our review of the literature, we expect an 84% progress ratio in mobile source industries. If the progress ratio (p) is 84%, the learning rate (b) would equal -.25. Information about cumulative output and forecasts of the number of units to be produced by the industry in the coming period and the number of organizations involved in production can be obtained from industry sources and trade associations.

Method 1

The first method requires knowledge of y_t, the unit cost of production at time t, but does not require knowledge of a, the costs required to produce the first unit.

We use Equation 1 to estimate the cost of production at a future point in time, y_{t+1}. From Equation 1:

$$y_t = a\, x_t^b$$
$$y_{t+1} = a\, x_{t+1}^b$$

Note that y_{t+1} is defined for the subsequent time period and not for when cumulative output doubles as in Equation 3. If we form a ratio of these two equations, the a terms cancel:

$$\frac{y_{t+1}}{y_t} = \left(\frac{x_{t+1}}{x_t}\right)^b$$

Rearranging terms, we solve for unit cost in the coming period, y_{t+1}:

$$y_{t+1} = \left(\frac{x_{t+1}}{x_t}\right)^b y_t \qquad \text{(Eq. 6)}$$

To illustrate this approach, assume that the following values of parameters were determined based on the literature and trade association data:

q_{t+1}	=	30,000 units to be produced in the coming year
x_t	=	100,000 cumulative units produced as of time (t)
x_{t+1}	=	130,000 cumulative units produced as of time (t+1)
b	=	-.25
y_t	=	68

Inserting these values into Equation 6, we calculate:

$$y_{t+1} = (130{,}000/100{,}000)^{-.25}(68) = 63.7$$

That is, the unit cost of production at time (t+1) would equal $63.70. Thus, for an 84% progress ratio (which corresponds to a learning rate of -.25) and for the values of parameters noted above, the unit costs of production would decline from $68.00 in one period to $63.70 in a subsequent period.

Method 2

In contrast to Method 1 which requires an estimate of the current cost, y_t, but does not require an estimate of the initial cost of production, a, Method 2 requires an estimate of the initial cost, a, but not of current costs, y_t. For Method 2, we compute costs according to Equation 1:

$$y_{t+1} = a x_{t+1}^{b}$$

To illustrate the approach, we introduce the estimate of a = 1,200 and assume x_{t+1} = 130,000 and b= -.25, as in Method 1. Inserting these values into Equation 1, we obtain:[29]

$$y_{t+1} = (1{,}200)(130{,}000)^{-.25} = 63.2$$

Thus, the unit cost of production in year (t+1) would be $63.20. This is a dramatic decrease from the initial value of $1,200. The intuition behind the dramatic decrease is that cumulative output would have doubled very many times from the start of production to the current period (e.g., from 1 to 2 units, from 2 to 4, from 4 to 8, 8 to 16 and so on).

Which method to use would depend on whether one had more confidence in estimates of current costs or of the initial cost. If one had more confidence in estimates of current costs than the initial cost, Method 1 would be preferable to Method 2. Conversely, if one had more confidence in estimates of initial costs than current costs, Method 2 would be preferable. In addition, if a product is just going into production, Method 2 would be appropriate.

Both methods have the advantage of applying to organizations (and industries) that are mature as well in early stages. The power function that underlies the learning curve has the property that the rate of learning is the same for each doubling of cumulative output. It would take longer for cumulative output to double in mature industries than in nascent industries but the effect of the doubling would be the same. For example, going from producing 100,000 to 200,000 units would typically take longer than going from 100 to 200 units. The rate of improvement in both cases, however, would be the same.

Both methods require forecasts of the number of units that will be produced in a future time period. In most instances, such forecasts would be more readily obtained than forecasts of when cumulative output will double. In addition, firms are often interested in forecasting their costs at a future point in time. If one had access to good forecasts of when cumulative output would double and estimates of current costs, one could compute the costs when cumulative output doubled, y_2, from Equation 3.

[29] These numbers were chosen for illustrative purposes. If we had both the number required by Method 1 and the number required by Method 2 from the same firm, results would be consistent across the two methods.

Appendix B. Summaries of Articles that Received a Detailed Review

Contents

Agrawal, A. & Muthlingam, S.

Article	**Does organizational forgetting affect vendor quality performance? An empirical investigation**
Publication	*Manufacturing & Service Operations Management*, Articles in Advance, pp. 1–18
Date	2015
Industry examined	Car manufacturer vendors
Research question(s)	• How does organizational learning and organizational forgetting affect vendor quality performance? • What factors influence the impact of such learning and depreciation?
Type of learning examined	Organizational forgetting; Two mechanisms of organizational learning: (1) learning-by-doing (autonomous learning) and (2) quality improvement initiatives (induced learning); Location of knowledge
Data sources	• Actual data from an unidentified large automotive manufacturer in Asia (for confidentiality reasons) • Interviews with senior managers and engineers of the manufacturer and its suppliers
Data size	• 2,732 quality improvement initiatives implemented by the car manufacturer's 295 vendors • 43 semi-structured interviews
Data years	2006–2009
Data adjustment	• The *defect rate* is calculated as the number of defective parts per million received divided by total parts supplied multiplied by 10. • *Lagged cumulative production experience* is the lagged number of units (in hundred thousands) supplied by the vendor.
Methodology	The authors estimate Eq. 4 to assess the impact of organizational learning. $(4) ln(Y_{it}) = a_i + f3_p P_{i(t-1)} + y_Q Q_{i(t-1)} + 17_i V_i + < /_i M_t + lf_i C_t + E_{it}$ Where, Y_{it} – defect rate $f3_P$ – learning rate for production experience $P_{i(t-1)}$ – lagged cumulative production experience y_Q – learning rate for quality improvement experience $Q_{i(t-1)}$ – lagged cumulative quality improvement experience V_i – vendor fixed effects M_i – product mix and model change controls C_t – time fixed effects E_{it} – error terms *i* – vendor *t* – time The authors estimate Eq. 5 to assess the impact of organizational forgetting. $(5) ln(Y_{it}) = a_i + f3_p AK_{i(t-1)} + y_Q IK_{i(t-1)} + 17_i V_i + < /_i M_t + lf_i C_t + E_{it}$

	Where, $AK_{i(t-1)}$ – stock of autonomous knowledge in the prior period $IK_{i(t-1)}$ – stock of induced knowledge in the prior period The authors estimate Eq. 6 to evaluate the impact for quality improvement initiatives. The authors estimate Eq. 7 to include organizational forgetting. (7) $ln(Y_{it}) = a_i + f3_p AK_{i(t-1)} + y_S KS_{i(t-1)} + y_R KR_{i(t-1)} + y_D KD_{i(t-1)} + 17_i V_i + </_i M_t + lf_i C_t + E_{it}$ Where, KS_{it}, KR_{it}, and KD_{it} – induced knowledge stock related to quality assurance, process improvement, and design quality initiatives, respectively The authors estimate Eq. 8 to evaluate the impact of where quality knowledge gets embedded. The authors estimate Eq. 9 to include the impact of organizational forgetting. (9) $ln(Y_{it}) = a_i + f3_p P_{i(t-1)} + y_{TS} KTS_{i(t-1)} + y_{RS} KRS_{i(t-1)} + y_{OS} KOS_{i(t-1)} + 17_i V_i + </_i M_t + lf_i C_t + E_{it}$ Where, KTS_{it}, KRS_{it}, and $KOS_{it,}$ – induced knowledge stock related to quality improvement projects with technology, routines, and operator solutions, respectively.
Statistical methods used	• To estimate Eqs. 4, 6, and 8, the authors use panel data regression. They use clustered standard errors in line with Wooldridge (2002). • To estimate Eqs. 5, 7, and 9 the authors use an approach that builds on the nonparametric bootstrap technique proposed by Freedman (1981) and discussed in Davidson and MacKinnon (2006). The technique involves simultaneously doing a 2-dimensional grid search over A_P and A_Q and bootstrapping.

Results	To assess the impact of organizational learning and forgetting (Eqs. 4 & 5):
	• Quality performance improves with cumulative production experience and cumulative quality improvement experience (i.e., both autonomous and induced learning contribute to enhanced vendor quality).
	• The estimated coefficient for organizational forgetting for autonomous learning is .9855. Gains from autonomous learning depreciate by 16.08% every year (=1-$.9855^{12}$)
	• The estimated coefficient for organizational forgetting for induced learning is .9893. Gains from induced learning depreciate by 13.17% every year (=1-$.9883^{12}$)
	
	To evaluate the impact for different types of quality improvement initiatives (Eqs. 6 & 7):
	• Without accounting for organizational forgetting:
	    o Quality performance improves with cumulative production experience.
	    o Estimates of organizational learning are significant only for quality assurance and process improvement initiatives (not design quality).

	• Accounting for organizational forgetting:
	  o Improvement in quality performance driven by quality assurance initiatives does not depreciate over time.
	  o Process improvement depreciation is estimated at .9872. Gains obtained from doing process improvement projects depreciate by 14.32% every year (=1-.9872^{12}, since the .9872 represents the monthly depreciation parameter).
	
	To evaluate the impact of where quality knowledge gets embedded. (Eqs. 8 & 9):
	• Without accounting for organizational forgetting:
	  o Lagged cumulative technology, routines, and operator solutions contribute to organizational learning.
	• Accounting for organizational forgetting:
	  o Estimates of organizational forgetting for lagged cumulative technology solutions (.9923), for lagged cumulated routines solutions (.9873), and for lagged cumulative operators solutions (.9752) are significant. Hence, quality gains obtained from quality improvement initiatives that focus on technology, routines, and operators depreciate by 8.86%, 14.22%, and 26.02% per year, respectively.

Assessment	To assess the impact of organizational learning and forgetting:
	• The results are significant.
	• Quality gains obtained from organizational learning are substantial even after accounting for the impact of organizational forgetting.
	• Induced learning provided nearly a 2.5 times larger annual net defect reduction than autonomous learning.
	• The annual depreciation of quality gains, which ranged from 13% to 16%, was lower than depreciation rates estimated in other studies. The authors attribute this to two factors:
	  o Quality performance is often better documented and tracked from the outset of production than are measures of productivity and cost.
	  o There was negligible turnover of Supplier Improvement Unit engineers during the analysis period.
	
	To evaluate the impact for different types of quality improvement initiatives:
	• Without accounting for organizational forgetting:
	  o The estimates of organizational learning are significant only for quality assurance and process improvement initiatives.
	• Accounting for organizational forgetting:
	  o The estimate of organizational forgetting in quality assurance is not significant.
	  o The authors do not make inferences about organizational forgetting for design quality, as the relevant organizational learning estimates are not significant.
	
	To evaluate the impact of where quality knowledge gets embedded:
	• All estimates are significantly different from one.

Conclusions	• Organizational forgetting affects quality gains obtained from learning-by-doing (autonomous learning) and quality improvement initiatives (induced learning).

	o 16% of quality gains from learning-by-doing and 13% of quality gains from induced learning depreciate every year. • The impact of organizational forgetting differs across the types of quality improvement initiatives. o Quality gains from process improvement initiatives depreciate by more than 14% per year. o Quality gains from quality assurance initiatives do not depreciate. o Significant organizational learning estimates for design quality initiatives were not observed. • The impact of organizational forgetting depends on where quality knowledge was embedded. o Depreciation is lower for knowledge embedded in technology (9%) than for knowledge embedded in organizational routines (14%) or organizational members (26%). • The results suggest the need for continued attention to sustain and enhance quality performance in supply chains.
Future research	• Consider costs incurred by vendors to implement quality improvement initiatives. • Observe solutions that were not implemented. • Investigate whether all modes of organizational forgetting identified by de Holan and Phillips (2004) (i.e., dissipation, degradation, purging, and suspension) are relevant in the quality domain.
Other notes	Definition of terms used in the article: • Learning-by-doing/autonomous learning – improving quality by performing the same task repeatedly • Quality improvement initiatives/induced learning – undertaking conscious actions to improve quality • Quality assurance initiatives – its principal focus is introduction or modification of vendor inspection procedures • Process improvement initiatives – its principal focus is changes or modifications to vendor production processes • Design quality initiatives – its principal focus is changes or modifications to the design of the components manufactured by vendors • Technology solution initiatives – address quality issues by introducing new equipment, modifications to existing equipment, changes to materials, or changes in design • Routine solution initiatives – focus on changes to repetitive patterns of work or introduced new repetitive activity • Operator solution initiatives – address quality issues primarily by developing or improving operator skills via training and monitoring
Applicability of results	This study did inform EPA's learning rate estimate. The study is related to the mobile source sector and the methodology used to determine progress ratios was consistent with other studies that measured learning and forgetting in terms of improvements in quality performance (i.e., the defect rate)—not unit costs.
Themes	Organizational learning, Organizational knowledge depreciation, Disaggregation of learning and knowledge depreciation, Location of knowledge (e.g., embedded in technology)

Argote, L.

Article	**Chapter 3: Organizational forgetting**
Publication	*Organizational learning: Creating, retaining and transferring knowledge*. Springer.
Date	2013
Industry examined	Secondary analysis of studies on aircraft, ship, and automotive production as well as fast food franchises.
Research question(s)	• Does organizational knowledge acquired through learning by doing persist through time or does it depreciate? • Why might knowledge depreciate? • Could the departure of key people affect organizational performance?
Type of learning examined	Organizational learning by doing; Organizational forgetting
Data sources	Results from three production programs were summarized: results from the Lockheed L-011 TriStar aircraft study as reported in Argote and Epple (1990) and Benkard (2000); results from the production of Liberty ships during World War II as reported in Rapping (1965) and Argote, Beckman, and Epple (1990); and results from a study of fast food franchises as reported in Darr, Argote, and Epple (1995). In addition, new results were presented from study of a North American truck plant (Argote, Epple, Murphy & Rao, 1997). The plant is unionized with about 3,000 employees and has extremely advanced technology.
Data size	Unspecified
Data years	The Lockheed L-011 TriStar aircraft study: 1972–1981 The shipyard study: 1941–1943 The automotive study: Weekly data over a 2-year period from the start of production at the plant. Exact years unspecified. The franchise study: Weekly data. Exact years unspecified
Data adjustment	None
Methodology	The Lockheed L-011 TriStar aircraft study: • Argote and Epple (1990) pieced together data on production from publically available data (e.g., newspapers, trade publications, annual reports), showed that data did not fit the classic learning curve, which assumes knowledge is cumulative, suggested depreciation occurred, and discussed factors that could have contributed to depreciation. • Benkard (2000) obtained detailed data from Lockheed and determined empirically that a model that allows knowledge to depreciate explained the data better than the conventional model that assumes that knowledge is cumulative and persists through time. The shipyard study: • Rapping (1965) had convincingly demonstrated that learning occurred in the production of Liberty ships during World War II. His study advanced the state of the art at the time by controlling for economies of scale and finding strong evidence of learning when variables measuring economies of scale were included in the statistical models.

	• Argote, Beckman and Epple (1990) built on Rapping's work by investigating whether knowledge depreciated over time and whether knowledge transferred across the different shipyards. • Estimated production functions in which output produced in a given period depended on the inputs of labor, capital, organizational experience, and other variables (3.1) $ln(q_{it}) = a_0 + \left(\sum_{i=2}^{13} a_i D_i\right) + \alpha \ln(H_{it}) + \beta \ln(W_{it}) + \gamma ln(K_{it-1}) + \delta' Z_{it} + u_{it}$ Where, $K_{it} = \lambda K_{it-1} + q_{it}$ q_{it} – tonnage (in thousands) produced in yard *i* in month *t* D_i – dummy variables for each shipyard (to control for unmeasured yard-specific factors) H_{it} – labor hours (in hundreds) in yard *i* in month *t* W_{it} – shipways used in yard *i* in month *t* K_{it} – knowledge acquired in yard *i* through month *t* λ – depreciation parameter (λ<1 implies depreciation) • The authors tested alternative models which compared cumulative output and time. The automotive study: • Estimated a production function The franchise study: • Unspecified
Statistical methods used	Not specified

Results	The Lockheed L-011 TriStar aircraft study:
	• Possible factors for why unit costs rose with increasing experience:
	  o The program was plagued by shortages of personnel and parts, strikes, deregulation, and high fuel prices.
	  o Lockheed attempted to increase production dramatically in the late 1970s and hired many workers without previous experience in aircraft construction and without high school diplomas.
	  o Competitors had a larger experience base from which to learn and improve.
	• Benkard (2000) confirmed that knowledge depreciation occurred in his empirical study.
	
	The shipyard study:
	• Organizational learning occurred. With each doubling of the cumulative number of ships produced, the unit cost of production declined to 74% of its former value.
	• There appears to be a rapid rate of knowledge depreciation. The estimated rate ranged from .70 to .85, which implies that from a stock of knowledge available at the beginning of a year, only 1.4% (=$.70^{12}$) to 14.2% (=$.85^{12}$) would remain 1 year later.
	• The coefficient on the calendar time variable was negative, which indicated that

	the passage of time did not explain productivity gains. When a more general translog specification of the production function was used, the coefficient was smaller in magnitude and statistically insignificant. The automotive study: • When the depreciation parameter was constrained (i.e., the conventional learning curve model): o Provided strong evidence of learning at the plant (i.e., production increased significantly with rising cumulative output) o There were constant returns to labor hours and output increased proportionately with the number of shifts worked. • When the depreciation parameter was not constrained: o Monthly depreciation parameter = .989 • When a time explanatory variable was added: o There was evidence that the plant became more productive over time. o The experience variable remained highly significant. o The estimated value of the depreciation parameter decreased. • When analyzing the relationship between personnel movement into the plant and productivity: o Found an inverted-U relationship between the number of new hires moving into the plant and the plant's productivity (increases in productivity were observed up to 38 people, 1%–2% of the workforce, per week) o Turnover of high-performing employees appeared to negatively affect the organization's productivity; turnover of low-performing employees might have improved the organization's productivity, but the variable of the number of employees discharged for poor performance was not consistently significant. o Turnover of the third group whose reason for leaving was not performance related, was not significantly related to productivity. o The rate of learning did not change in the production environment (i.e., the quadratic form the learning variable was not significant. o Progress ratio: 83%. Each doubling of cumulative output at the plant led to a 17% reduction in unit cost. The franchise study: • The estimated weekly depreciation parameter ranged from .80 to .83 (Darr et al., 1995). This implies that roughly half of the knowledge stock available at the beginning of a month would remain at the end of the month.
Assessment	The Lockheed L-011 TriStar aircraft study: • The classic learning curve model that assumes knowledge is cumulative is too simplistic to capture the dynamics of organizational learning. The shipyard study: • The authors repeated the study using a translog specification and the results reinforced the results regarding knowledge depreciation. • When input effects and economies-of-scale effects are controlled for, strong evidence of learning and knowledge depreciation remain. The automotive study:

	• The evidence of learning is strong. • Movement of new employees into the plant at moderate levels appears to help productivity. • Turnover of high-performing employees appears to hurt productivity. • There appears to be a relatively permanent component to organizational memory that does not evidence depreciation (i.e., knowledge embedded in the organization's procedures and routines). • There appears to be a more transitory component of organizational memory that experiences a faster depreciation rate, which could be declarative knowledge (i.e., knowledge of facts). The franchise study: • The estimated rate of depreciation was the most rapid found in the literature.
Conclusions	• Knowledge acquired through learning by doing depreciates. • Recent experience is a more important predictor of current productivity than experience in the distant past. • Possible causes of knowledge depreciation: o Products or processes change and thereby render old knowledge obsolete. o Organizational records are lost or become difficult to access. o Member turnover o Uneven rates of production, which can lead to forgetting by individuals • Knowledge depreciation seems to depend on an organization's technological sophistication (knowledge embedded in technology may be more resistant to depreciation than in other repositories) and the extent of labor turnover (high levels make it difficult to retain knowledge).
Future research	• Why do depreciation rates vary? • What is the role of labor turnover in knowledge depreciation? • Under what conditions does knowledge depreciate in organizations and what factors affect the rate of depreciation?
Other notes	The authors investigated different types of turnover: (1) Promotion - turnover of high-performing employees who left the plant because they were promoted; (2) Discharge - turnover of employees who were discharged for poor performance; and (3) All other reasons employees departed that were not a function of performance (e.g., retired, deceased, quit).
Applicability of results	This study did not inform EPA's learning rate estimate because it is a secondary analysis of other studies related to learning by doing and it does not estimate any progress ratios based on original data.
Themes	Organizational learning by doing, Organizational forgetting, Determinants of organizational forgetting, Knowledge depreciation

Argote, L., & Epple, D.

Article	**Learning curves in manufacturing**
Publication	*Science*, Vol. 247, No. 4945, pp. 920-924
Date	1990
Industry examined	A thought piece on studies from several disciplines; focuses on manufacturing
Research question(s)	• Why do some organizations show rapid rates of learning and why do others fail to learn? • Identify factors affecting organizational learning curves.
Type of learning examined	Organizational learning by doing; Organizational forgetting; Knowledge transfer
Data sources	A selection of empirical studies of organizational learning curves in manufacturing (focused on organizations or work groups)
Data size	Unspecified
Data years	Unspecified
Data adjustment	None
Methodology	Qualitative summation of previous literature
Statistical methods used	None
Results	The studies reviewed suggest organizational learning rates vary for the following reasons: • Organizational forgetting o Unit costs are often higher than level achieved before interruptions such as strikes, material shortages, and fluctuations in product demand. o Knowledge acquired through learning by doing depreciates for reasons such as: individuals forget how to perform tasks; individuals are replaced by others with less experience through turnover; changes in products or processes that make previously acquired knowledge obsolete; organizational records or routines are lost or become difficult to access. • Employee turnover o It matters more in organizations where jobs are not standardized and procedures do not exist for transmitting knowledge to new members. o Turnover of managers and technical support staff (e.g., engineers) matter more than turnover of direct production workers. • Transfer of knowledge across products and across organizations o Transfers across organizations might occur through personnel movement, communication, participation in meeting and conferences, training, improved supplies, modifications in technology, or reverse-engineering of products. • Incomplete transfer within organizations • Economies of scale o Estimating the rate of learning without controlling for the changing scale of operation can result in an overestimation.

Assessment	N/A
Conclusions	• The knowledge about which factors affect organizational learning curves can be used to improve manufacturing performance. • Organizations vary considerably in the rate at which they learn and identify factors responsible for the variation. • Issues that need to be considered during selection of functional form: o Choice of variables, which varies according to the production process being studied o Specification of the properties of random factors affecting the production process o Appropriate method of estimating the parameters of interest
Future research	N/A
Other notes	• Organizational learning curves focus on the performance of entire organizations or organizational subunits in contrast to the performance of individuals. • There is often more variation across organizations or organizational units producing the same product than within organizations producing different products.
Applicability of results	This study did not inform EPA’s learning rate estimate because it is a secondary analysis of other studies related to learning by doing and it does not estimate any progress ratios based on original data.
Themes	Sources of variation in learning rates, Organizational forgetting

Bahk, B.-H., & Gort, M.

Article	**Decomposing learning by doing in new plants**
Publication	*Journal of Political Economy*, Vol. 101, No. 4, pp. 561–583
Date	1993
Industry examined	New plants in 15 manufacturing industries which include: bottled and canned soft drinks; sawmills, planning mills; mobile homes; corrugated, solid fiber boxes; commercial printing, lithographic; industrial gases; paints and allied products; petroleum refining; metal cans; fabricated structural metal; electronic computing equipment; refrigeration, heating equipment; radio, TV communication equipment; semiconductors, related devices; and motor vehicle parts, accessories. 41 industries were used as a robustness test. Refer to Appendix Table A1 for the complete list.
Research question(s)	• What is the magnitude of firm-specific learning by doing (in the context of a production function that distinguishes the effects of such learning from the accumulation of labor, general human capital, physical capital, and embodied technical change)? • Over which time intervals do the three elements of firm-specific learning by doing (i.e., organizational learning, capital learning, and manual (labor) task learning) accumulate?
Type of learning examined	*Firm-specific* learning by doing (Note, this concept differs from the typical concept of learning by doing. See the “Other notes” section.)
Data sources	U.S. Bureau of the Census, Longitudinal Research Database

Data size	A set of time-series and cross-section data
	• The 15-industry sample
	  o Consists of 1,281 plants born 1973 or later; Excludes plants born 1983 or later because not enough time had passed to capture the learning effects
	  o 7,064 observations in the time-series and cross-section pool from 1973–1986. The data were predominantly cross-sectional.
	• The 41-industry sample
	  o Consists of 2,150 plants born 1973 or later
	  o Consists of the 15 industries and those with too few plants to carry out the analysis at the industry level. Each industry had at least 16 plants.

Data years	1973–1986. The average length of a panel was between 6 and 7 years.
Data adjustment	Capital: • Variable was lagged half a year. • The authors added the capitalized value of the changes in rentals of fixed assets to the cumulative total of gross capital expenditure. • Used a capital expenditure deflator for the year preceding the plant’s birth for plants that had initial capital stock that preceded their birth. Output • Output was proxied by data for shipments and value added, each deflated by an appropriate deflator for the relevant 4-digit industry.
Methodology	Instead of using a progress function, which defines learning by doing as the change in unit costs over time, the authors view learning by doing as a productivity-enhancing

	factor in a conventional production function. The authors introduce separate arguments in the production function for embodied input-augmenting technical change (labor, human capital, physical capital, and vintage). The authors proxy firm-specific learning by doing using cumulative output per employee (or per unit of physical capital), and by time elapsed since the organization's birth. (6) $\log(Y_{it}) = \beta_1 + \beta_2 \log(L_{it}) + \beta_3 \log(W_{it}) + \beta_4 \log(K_{it}) + \beta_5 \log(X_{it}) + \beta_6 V_{it} + \beta_7 t + U_{it}$ Where, Y – output measured by shipments (or measured by value added) L – "pure" labor measured by the number of employees W – human capital measured by the average wage rate K – gross stock of physical capital X – index of accumulated experience V – weighted average vintage of the capital stock with ascending values for more recent vintage *t* – chronological time in years *i* – plant The authors used the following equation to decompose learning by doing into its principal elements (with the exception of manual/labor learning): (7) $\log(Y_{it}) = \beta_1 + \beta_2 \log(L_{it}) + \beta_3 \log(W_{it}) + \beta_4 \log(K_{it}) + u_{it}$ Where all of the variables are the same as in Eq. 6 with the exception of *t*, which is the amount of time elapsed from the birth of a plant. Learning is now captured by shifts in the β's across successive *t's*. Note, that the authors used the 15-industry sample, which they tested twice. First, the test had 399 plants (assumed 8 consecutive years of operation). The second test had 237 plants (assumed 10 consecutive years of operation). The dependent variable, output, is measured by shipments.
Statistical methods used	Regression using (pooled) time-series and cross-section data

Results	From the pooled 15-industry sample:
	• Increases in output attributed to industry-wide learning by doing (i.e., increases in the knowledge stock) are uniquely related to embodied technical change of physical capital (and perhaps human capital, but this was not tested).
	• Using the following proxies for firm-specific learning by doing:
	  o Cumulative gross output since birth: A 1% increase results approximately in a 0.03% increase in output (Models i–iii).
	  o Cumulative gross output since birth divided by the average number of employees at the plant (i.e., cumulative output per unit of labor input): A 1% increase results in a 0.079% of increase in output (Model iv).
	  o Number of years from the birth of the plant: Each additional year results in 1.2% rise in output per year.

	• Embodied technical change of capital is associated with a 2.5%–3.5% change in output for each 1-year change in average vintage.
	• The elasticity of output with respect to "pure" labor was roughly the same as that with respect to human capital.
	
	From the industry-specific sample of the 15 industries:
	• Confirms the results from the pooled data
	• The coefficients for the key inputs showed considerable variability between industries.
	• In the "Motor Vehicle Parts, Accessories" industry (SIC 3714), when firm-specific learning by doing is proxied by cumulative gross output since birth, a 1% increase results in a 0.025%-increase in output, which is equivalent to a progress ratio of 0.98.
	
	From the pooled 41-industry sample:
	• The results were similar when the dependent variable, output measured by shipments, was interchanged with output measured by value added, but the fit was better with the former proxy.
	• Estimated coefficients are similar to those in the 15-industry samples.
	• Using the following proxies for firm-specific learning by doing:
	  o Cumulative gross output divided by the 1982 book value of gross physical capital at the plant (i.e., cumulative output per unit of capital input): A 1% increase results in approximately a 0.08%-increase in output as measured by shipments (Model vi).
	  o Cumulative gross output divided by the 1982 number of employees at the plant (i.e., cumulative output per unit of labor input): A 1% increase results in approximately a 0.149%-increase in output as measured by shipments (Model vii).
	
	From distinguishing between the elements of firm-specific learning by doing:
	• Capital learning continues until the 5th or 6th year after the birth of a plant. Initially, the productivity of capital varies greatly across plants.
	• Organizational learning is reflected in the coefficients of "pure" labor and human capital.
	  o There appears to be a steady rise in the elasticity of output with respect to labor input that continues through at least the 10th year after a plant's birth (with the exception of the first 2 years which is likely due to the distorting effect caused by unequal rates of capital learning).
	  o The effect of human capital is more erratic. Using a 3-year moving average, there appears to be rise in the elasticity of output with respect to human capital from the 4th to 8th year (with the exception of the first 2 years which is likely due to the distorting effect caused by unequal rates of capital learning).
	• Overall, productivity continues to rise for a considerable number of years after a plant's birth.

Assessment	From the pooled 15-industry sample: • The results are significant. However, the high R^2 values may be due to the mostly cross-sectional data and the large difference in plant sizes. • Model iv, uses cumulative output per unit of labor input—an independent variable that has been standardized to avoid simply capturing plant scale. From the pooled 41-industry sample: • The estimated coefficient on cumulative output per unit of capital is higher than for the cumulative output per unit of labor. • There is a higher estimated coefficient for learning when output is measured by shipments than when it is measured by value added. The most plausible explanation lies in measurement errors associated with deriving value added. Specifically, in the measurement of costs of materials and from inconsistencies over time in the valuation of semi-finished and finished product inventories. From distinguishing between the elements of firm-specific learning by doing: • The R^2 values rise as the time since birth elapses. This indicates that the consistency of the relationship between inputs and output rises with learning. • At first, the productivity of capital varies greatly across plants; likely because capital goods are not initially installed in balanced systems.
Conclusions	• Industry-wide learning appears to be uniquely related to embodied technical change of physical capital. But once physical capital is accounted for, industry-wide learning is no longer a significant explanatory variable. • Firm-specific learning is a significant explanatory variable. • Organizational learning appears to continue over a period of 10 years following a plant's birth. • Capital learning continues for 5 to 6 years following a plant's birth. • Hence, new entrants incur costs that established organizations no longer face.
Future research	Include the possibility for interplant learning spillovers

Other notes	• The authors separate learning into two forms of knowledge and skill accumulation. The first form consists of accumulation that requires an investment (e.g., hiring, training programs, R&D expenditures). The second form, learning by doing, is a by-product (or joint product) of production of goods and services.
	• Learning by doing costs less than knowledge acquired under the first form (gives older firms an advantage over new entrants).
	• Returns to general human capital are reflected in the wage rate. Firm-specific learning by doing is not captured by labor and enters into the firm's stock of organizational capital.
	• According to the authors, firm-specific learning by doing is an aspect of disembodied technical change (i.e., in that it is reflected in neither the labor nor the capital inputs but rather explains differences across firms or plants in the productivity of the same levels and types of inputs)
	• A plant was deemed "new" if there were no records for it prior to 1972.
	• Definitions of terms used in the article:
	  o Manual task/Labor learning
	    ▪ The routinization of tasks and adaptation to tasks that are peculiar to individual plants/firms. (Does not capture the acquisition of general skills through experience.)
	    ▪ This should be reflected in the productivity of the labor input, but the data used were not suitable for capturing this effect. The data used did not effectively distinguish between organizational and manual learning.
	  o Capital learning
	    ▪ Increases in knowledge about the characteristics of given physical capital (e.g., engineering information that accumulates through experience on the tolerances to which parts are machined, on the use of special tools and devices, and on improvement in plant layouts, and the routing and handling of materials, the true capacity of equipment, on required maintenance, how to avoid breakdowns).
	    ▪ This is reflected mainly in the productivity of the capital input.
	  o Organization learning
	    ▪ The matching of individuals and tasks based on knowledge derived from experience of the capacity/limitations of employees, the accumulation of interdependent knowledge about production possess by team members (not portable by any one team member), the development of interactions among employees, and managerial learning reflected in improved scheduling and coordination among departments and in the selection of external suppliers.

Applicability of results	This study did not inform EPA's learning rate estimate because it estimates progress ratios for industries, one of which (i.e., Motor vehicle parts, accessories) is related to the mobile source sector. Note that this study uses shipments as a dependent variable when estimating the progress ratio, which may not be a good measure of productivity because firms often keep output in inventory before shipping it. The other dependent measure used was value added, which is problematic for our purposes because measures such as value added that embody price can confound supply-side learning with demand-side changes that are unrelated to learning. The problem of confounding supply- and demand-side learning might also apply to their shipment variable because

	it appears to be expressed in dollar values rather than number of shipments: "Output was proxied alternatively by data for shipments and for value added, each deflated by an appropriate deflator for the relevant four-digit industry (p. 580)."
Themes	Estimation of the learning rate, Persistence of firm-specific learning by doing, Disaggregation of learning's elements

Balasubramanian, N., & Lieberman, M. B.

Article	**Industry learning environments and the heterogeneity of firm performance**
Publication	*Strategic Management Journal*, Vol. 31, No. 4, pp. 390–412
Date	2010
Industry examined	U.S. manufacturing sector
Research question(s)	What is the rate of learning (overall and by industry)? Two hypotheses are established: • H1: The rate of learning by doing, as measured by the slope of the learning curve, will be higher in industries with greater complexity. • H2: The heterogeneity of firm performance will be greater in industries with higher rates of learning.
Type of learning examined	Learning from direct operating experience (i.e., learning by doing)
Data sources	• The U.S. Census Bureau – to estimate the industry learning rate. • Compustat – to estimate the cross-sectional variation in business performance within an industry, after applying the industry learning rates estimated using U.S. Census Bureau data to Compustat's firm data.

Data size	The U.S. Census Bureau; The Longitudinal Research Database
	• Combines data with a link from:
	  o Census of Manufacturing
	    ▪ Plant-level data on all U.S. manufacturing plants with at least one employee (over 55,000 plants over 1973–2000)
	  o Annual Survey of Manufactures
	    ▪ Data from a sample of U.S. manufacturing establishments
	    ▪ Place considerable weight on large plants and plants belonging to multi-plant firms
	    ▪ Every year, a sample of new entrants is added
	• Data is subject to access restrictions and disclosure constraints (e.g., no data can identify or relate to a single firm or plant)
	• Contains over 4 million plant-year observations from 1963–2001
	• Sample selection criteria:
	  o Eliminated all plants established before 1973 or after 1997
	    ▪ 1973 is the first year of the Annual Survey of Manufactures (ASM); therefore, it is not possible to "reliably obtain the entry year for plants that first appear in the 1963, 1967, or 1972 censuses" (p. 397).
	    ▪ In 1997, the U.S. Census Bureau switched from the standard industrial classification code (SIC) to the North American Industry Classification System (NAICS). Plants established after 1997 were omitted to "minimize errors from industry misclassifications" (p. 397).
	  o Excluded all subsequent observations for a plant if the gap between consecutive survey years is longer than 2 years
	  o Removed all plants that have a primary industry specialization ratio (i.e., the output share of the primary 4-digit standard industrial classification (SIC) industry in the case of a multiproduct plant) of less than 75%

	o Dropped outlier plants that are in the top 0.5 percentile of capital-labor ratio or of growth in the number of employees, shipments, or capital expenditure • 182,603 plant-year observations Compustat • Firm data from firms that have a strictly positive total asset value • 1,523 industry-year observations
Data years	1973–2000
Data adjustment	The authors adjusted the Compustat data by aggregating firm-year level data to industry-year level: • For each firm-year observation, the authors compute: o Tobin's *q* (the ratio of market value of assets to book value of assets) o profitability (the ratio of operating profits before depreciation to total assets) • Eliminate all outlying observations in the top and bottom 1% in terms of firms' *q* or profitability • These data on firm performance are aggregated to obtain the dispersion in firms' *q* and profitability for each 3-digit SIC industry in each year.
Methodology	• Used the information-theoretic model (Jovanovic & Nyarko, 1995) (5) $\rho = \frac{(1-x_t-\sigma_w^2)^N}{(1-\sigma_w^2)^N}$ N – the number of process stages σ_w^2 – the noise arising at each stage o Describes three complexities ▪ N – The greater the number of tasks that any production activity requires, the greater the number of decisions involved, and the higher the complexity. ▪ σ_w^2 – The variance of θ; the uncertainty surrounding the optimal way to perform the activity ▪ w – The importance of transitory disturbances. Decision makers can glean more useful information from each production run in contexts when there are low levels of disturbances than when there are high levels. • The authors note that the traditional method for measuring learning by doing requires cost and production data that might not be widely available. The authors use the approach of Bahk and Gort (1993), which replaces the variable, unit costs, traditionally used as the dependent variable in learning curve models with the variable, current period real value added, measured as real revenues minus real material expenses. • It is an extension of the Cobb-Douglas production function (capital, labor, and operating experience are considered inputs). (8) $Y_{ijt} = \Phi_{jt}(K_{ijt})^{\alpha_j}(L_{ijt})^{\beta_j}(X_{ijt})^{\lambda_j}v_{ijt}$ Y – current period real value added (real revenues less real material expenses) Φ – industry-wide improvements in productivity K – real capital stock L – quantity of labor X – prior cumulative output (a measure of experience) λ –industry learning intensity

	v – plant-specific term *i, j, t* – plant, industry, and year, respectively To estimate the importance of learning in Eq. 9, the authors used OLS to estimate the logarithmic version of Eq. 8. (9) $y_{ijt} = a_{jt} + \alpha_j k_{ijt} + \beta_j l_{ijt} + \lambda_j x_{ijt} + \varepsilon_{ijt}$ To formally test H1, (Unit of analysis – *plant* year) (10) $y_{ijt} = a_{jt} + \alpha k_{ijt} + \beta l_{ijt} + \lambda x_{ijt} + \lambda_1 C_{jt} x_{ijt} + \lambda_2 W_{jt} x_{ijt} + \lambda_3 R_{jt} x_{ijt} + \lambda_4 A_{jt} x_{ijt} + \varepsilon_{ijt}$ C – industry capital intensity (capital stock ÷ employment) W – industry wages R – industry R&D intensity (R&D expenditure ÷ sales) A – industry advertising intensity (advertising expenditure ÷ sales) To test H2, (Unit of analysis – *industry* year) (11) $\pi_{jt} = a_t + b\underline{\lambda_j} + c_1 R_{jt} + c_2 A_{jt} + c_3 C_{jt} + c_4 S_{jt} + c_5 N_{jt} + c_6 P_{jt} + \varepsilon_{ijt}$ π_{jt} – 90^{th}-10^{th} percentile range of firm performance, either firm's *q* or firm's profitability, in industry *j* during year *t* $\underline{\lambda_j}$ – estimated industry learning intensity R – industry R&D intensity (R&D expenditure ÷ sales) A – industry advertising intensity (advertising expenditure ÷ sales) C – industry capital intensity (total assets ÷ sales) P – average industry profitability (operating profits ÷ total assets) N – the number of firms in an industry S – industry size (total industry sales)
Statistical methods used	• To test the importance of learning, the authors used OLS regression. • To test H1, the authors used OLS to estimate Eq. 10 with plant fixed effects and instrumental variable specification as robustness checks.

Results	Estimated the importance of learning (Eq. 9, Models 1–4)
	• Model 1 – The production function did not estimate learning by doing.
	• Model 2 – Added prior experience
	  o Learning coefficient is 0.26, which implies a progress ratio of 0.84 (i.e., a 19.7% gain in productivity for every doubling of cumulative output)
	• Model 3 – Included 9,967 4-digit SIC industry-year dummies to control for all productivity improvements in each industry
	  o Learning coefficient is 0.23, which implies a progress ratio of 0.85 (i.e., a 17.3% gain in productivity for every doubling of cumulative output)
	• Model 4 (actually 117 different models for each SIC industry with 50+ plants) – Controlled for 3-digit SIC industry-wide productivity improvements
	  o There is significant variation in learning intensities across industries (just above 0 to almost 0.6)
	  o The average learning intensity is 0.22, which implies a progress ratio of 0.86 (i.e., a 16.5% gain in productivity for every doubling of cumulative output).

	To test H1 (Eq. 10, Models 5–10)
	• Models 5 and 6 – Used a larger sample, omitted industry R&D and advertising intensity terms. Model 5 included year indicators. Model 6 included industry-year dummies.
	  o The learning coefficient is higher in industries with greater capital intensity.
	  o The interaction effect of industry wages on prior experience becomes insignificant once industry-year effects are controlled for.
	• Model 7 – Used smaller sample, used industry R&D and advertising intensity terms
	  o The learning coefficient is significantly higher in industries with higher capital-labor ratios, as well as with greater R&D and advertising intensities.
	• Model 8 – Repeated Model 7, but assumed capital and labor coefficients were not fixed
	  o The results are not substantially different from Model 7.
	• Models 9 and 10 – Included plant fixed effects as robustness checks. Model 10 included direct terms.
	  o In Model 9, the direction and significance persist.
	  o In Model 10, the significance of interaction terms increases considerably and the direct terms are negative.
	  o When adding once-lagged instrumental variables, economic substance and significance were similar to Models 7 and 8.
	
	To test H2 (Eq. 11, Models 11–12)
	• Model 11 – Used the range of firm profitability as the dependent variable and the industry estimated learning coefficients
	  o The coefficient on industry learning intensity is 0.926; the difference in relative profitability between the best performers (top 10%) and the worst performers (bottom 10%) is considerably greater in industries with high learning.
	  o The coefficient on industry learning is positive and significant.
	• Model 12 – Same as Model 11, but used the range of firm *q* as the dependent variable
	  o Similar results as Model 11
	Robustness Checks:
	• Survivor bias, sample selection, R&D investments, measurement errors in capital, choice of production function form, and industry life cycle effects are not driving heterogeneity in learning rates.

Assessment	• The industry learning rate displays considerable heterogeneity across industries and it is positively correlated with the industry capital-labor ratio, R&D intensity, and advertising intensity. • Models 9 and 10 suggest that in industries with high capital, R&D, or advertising intensity, plant productivity is initially low but rises steeply with experience. • Industry learning intensity has a robust relationship with firm performance. Specifically, the cross-sectional variation in business performance within an industry, as measured by the interpercentile range (10^{th}–90^{th}) of firm *q* and firm profitability, is much greater in industries with higher learning intensities.

Conclusions	• Learning intensity is an important characteristic of the industry environment that should be considered in studies of firm and industry performance. • Industry learning intensity may explain competitive heterogeneity.
Future research	• Heterogeneity in products and learning rates within industries • Mechanisms of learning (e.g., training, engineering activities, routines) • The variation in the meaning and context of organizational learning across and within industries • Other forms of learning (e.g., knowledge transfer or spillovers -- learning from others) • Organizational forgetting • The mechanisms that explain the link between learning intensity and heterogeneity of firm performance • How variations in learning rates affect firm behavior • How variations in the knowledge acquisition processes across industries affect the observed heterogeneity
Other notes	The authors note that the model ignores a fourth dimension of complexity, the degree of interaction among the tasks. Interactions can greatly increase system complexity.
Applicability of results	This study did not inform EPA's learning rate estimate because the authors used real value added (i.e., revenues minus material expenses) as the dependent variable. Revenues are affected by many factors (e.g., sales, the economic climate) besides manufacturing costs.
Themes	Estimation of learning rate, Sources of variation in learning rates

Benkard, C. L.

Article	**Learning and forgetting: The dynamics of aircraft production**
Publication	*The American Economic Review*, Vol. 90, No. 4, pp. 1034–1054
Date	September 2000
Industry examined	Commercial aircraft
Research question(s)	Past empirical studies document learning-by-doing. The author tests this by applying it to commercial aircraft production. The author also tests the impacts of organizational forgetting and incomplete spillover of production expertise from one generation of production to the next.
Type of learning examined	Learning-by-doing; Knowledge depreciation; Knowledge spillovers
Data sources	Lockheed data made available to the author; L-1011 TriStar aircraft production
Data size	• 250 aircraft units produced during the production run (12 observations were removed because complete data for all levels of production were not available; hence, the author analyzed 238 aircraft units); • Data set includes labor requirements for each aircraft unit produced (i.e., direct man-hours)
Data years	1970–1984
Data adjustment	None
Methodology	The author modified the traditional learning curve specification by redefining experience to reflect organizational forgetting. The author used the Leontif production function: factors of production used in fixed proportions, no substitutability between factors. In this sector, labor and engines are the biggest inputs and neither can be substituted; capital stock is constant over time. The author also tested the suitability of using a Cobb-Douglas production function by adding input prices to the model: proxies price of oil (demand shifter) and wages and price of aluminum (cost shifters) (4) $lnL_i = lnA(\overline{K}) + \theta ln(E_i) + \gamma_0 ln(S_i) + \varepsilon_i$ Where, L – labor K – capital (is fixed) θ – learning rate (learning = $1\text{-}2^{\theta}$) E – experience (i.e., cumulative past output) γ – within period returns to production S – line speed Experience is cumulative past output (the traditional learning model): (5)$E_i = E_{i-1} + 1$ with $E_1 = 1$

	Incorporate forgetting and spillover (the general learning model): $$(7) E_i = \begin{cases} E_{1,t} & \text{if } i \text{ is type-1, -100,-200} \\ E_{500,t} & \text{if } i \text{ is type -500} \end{cases} \text{, where}$$ $$(8) E_{1,t} = \delta E_{1,t-1} + q_{1,t-1} + \lambda q_{500,t-1} \text{ and } E_{1,1} = 1$$ $$(9) E_{500,t} = \delta E_{500,t-1} + q_{500,t-1} + \lambda q_{1,t-1} \text{ and } E_{500,1} = 1$$ Where, δ – experience depreciation parameter λ – experience spillover parameter
Statistical methods used	• OLS cannot be used on the production function (Eq. 4) because experience and line speed are correlated with productivity shocks to labor. Therefore, each model used the following methods: o The traditional learning model uses two-stage least squares (2SLS) (Eq. 5) o The two general learning models use nonlinear estimators. ▪ Nonlinear estimator: Generalized Method of Moments model with a conditional moment restriction described by Hansen (1982) • Two variables were instrumented (i.e., line speed and experience). Instruments are present and lagged demand and cost shifters. Various lags included. o Demand shifters: GDP, price of oil, and time trend o Cost shifters: world aluminum price and US manufacturing wages
Results	Traditional learning hypothesis (Eq. 5; Regressions 1–5): • The model works better for Units 1–112 than for 1–238, with a learning rate of 30% and 18%, respectively. • Adjustments to the model to account for line speed, time, and changes in labor costs do not improve the explanatory power of the model. • Although including a calendar time variable, along with production experience, improved the fit and the standard error on the time variable, the sign of the coefficient indicated that technological change is negative, so the model was rejected. Production function specification (Eq. 5; Regressions 6–8): • Adding wages and prices does not improve the fit of the model. • The coefficient on wages is positive, which is unlikely. • Added a "scope" variable to account for two models, which improved the fit of the original model. Forgetting and spillover (Eqs. 7–9; Regressions 9–10): • The model has a good fit. • The learning rate is 36%. • The monthly depreciation parameter is .96, which implies 61% (=$.96^{12}$) of the firm's experience existing at the beginning of a year survives to the end of a year. • The coefficient measuring forgetting is estimated extremely precisely and is significantly different from one in all cases; thereby, strongly rejecting the hypothesis of no forgetting. • Adding in incomplete spillovers improves the fit. • The spillover parameter estimates that approximately 70% of the knowledge

	spilled over from one model to another (perhaps due to task overlap between the two models). The results were tested against alternative specification including wages and prices and the results were not significantly different.
Assessment	• The discrepancy between Units 1–112 and 1–238 is caused by the fact that the firm's experience is not being fully retained over time. This becomes apparent only when the production rates are uneven and new models are introduced. • Adding forgetting and incomplete spillovers into the general learning model, explains both halves of the data. • Depreciation is high (61% of firm's stock of experience existing at the beginning of a year survives to the next year). This could be an artifact of labor (e.g., low aircraft production rates, high turnover, job bumping resulting from "displacement rights"). • Estimated learning rate: 35%–40%. These "are much higher than those estimated under the traditional learning hypothesis. The reason for this is that learning is no longer relative to cumulative production, but is not relative to accumulated experience, which is constantly depreciating. […] The new learning rate implies that if experience were doubled, then labor requirements would fall by 35-40 percent" (p. 1049). • The hypothesis of *complete* spillovers is rejected. • Impacts of prices and diseconomies of scope are rejected. "[…] as a result of incomplete spillovers, the decision to bring out a new […] model can involve a significant setback in learning, and an associated large and immediate increase in variable costs. […] [I]t becomes evident that introducing new models is a costly endeavor, even within an existing aircraft program" (p.1051).
Conclusions	• Researchers need to include organizational forgetting in an assessment of production. • Forgetting may not be important to all industries where learning takes place. Aircraft and ship markets are peculiar in that the products are labor intensive, learning is thought to be important at the individual worker level, and there is high turnover. • There are incomplete spillovers of production expertise when switching to the production of a new model. • The number of models can have great impact on variable production costs.
Future research	• Test impacts of forgetting on other industries. • Identify conditions under which forgetting occurs (e.g., high turnover and layoffs). • Test whether the experience depreciation rate is under a firm's control (e.g., avoiding layoffs, priority to workers that have been laid off).
Other notes	• This market was chosen because the dynamics of production are complex and marginal costs of aircraft production do not always decrease over time. Note, previous studies concentrated on military, not commercial, aircraft, and thus are not subject to impacts of market forces. • Definitions of terms used in article: o Organization forgetting: a firm's stock of production experience depreciates over time. Implication of forgetting: recent production is more important

	than more-distant past production in determining a firm's current efficiency. o Experience spillovers: Whether experience spills over across firms or products is a function of how specific the firm's production experience is. If the skills required to build one model transfer to another model, then the firm would experience a setback in learning and higher production costs for the new aircraft program. • The author analyzed three counterfactual production schedules and found the optimal production run looks much like the actual one, which closely matched schedule deliveries. • A stochastic version of this model was estimated and yielded almost identical results to the deterministic version.
Applicability of results	This study is did inform EPA's learning rate estimate because it is related to the mobile source sector, it is based on primary data, and it uses labor input per unit as a dependent variable.
Themes	Estimation of learning rate, Knowledge depreciation, Knowledge spillovers

Bernstein, P.

Article	**The learning curve at Volvo**
Publication	*Columbia Journal of World Business*, Vol. 23, No. 4, pp. 87–95
Date	1988
Industry examined	Automotive industry
Research question(s)	• What might managers learn from the Volvo experience? • How did Volvo use a long-term organizational development (OD) program to meet the requirements of the auto market and its employees?
Type of learning examined	Management techniques (e.g., an increased level of employee involvement, modest use of new technology, and diffusing strategies between plants) aimed at reducing absenteeism
Data sources	Description of plant operations in Sweden from the author's point of view
Data size	N/A
Data years	Mid-1960s to 1970s
Data adjustment	None
Methodology	The author performed a case study of Volvo automotive plants to explain the evolution of how managers responded to absenteeism and retention problems at their plants during the 1960s and 1970s.
Statistical methods used	No statistical methods used
Results	• The "Spontaneous Trial Period" allowed plants to add to Volvo's socio-technical knowledge stock related to plant practices aimed at meeting the non-material needs of its workers to reduce absenteeism. • After conducting over 1,000 interviews with employees at the Torslanda plant, which participated in the Spontaneous Trial Period, Volvo was able to take their opinions into account when devising new practices at new plants. • During the "Socio-Technical Strategy Period," Volvo employed solutions that were tailored to problems at each plant such as creating teams and handing over supervisory and quality control responsibilities to them, providing monetary incentives for learning new skills, creating low supervisor to worker ratios, and using team leaders and craftsmen to teach and integrate newcomers. • Volvo came up with OD programs (e.g., the Match Project, *Full Rulle*, and *Dialog*) to create a system-wide focus on the growth and development of its entire workforce. These OD programs are described in more detail in the "Other notes" section.
Assessment	N/A

Conclusions	• Learning at all levels was the key to Volvo's success. • Pragmatic trial and error and the diffusion of successful practices became a hallmark of the new system. • Throughout the Spontaneous Trial Period and the Socio-Technical Strategy Period, Volvo "moved down the learning curve as its managers built on earlier success and reduced errors" (p. 87), which resulted in improved productivity, better quality, and lessened absenteeism. • Based on Volvo's experience, the author suggested practices managers should consider to improve productivity and the quality of their products as well as to reduce absenteeism (e.g., diffusing industrial knowledge between plants; communicating corporate values and objectives clearly and consistently; and investing in the workforce's education and skill development).
Future research	N/A
Other notes	Definitions of terms used in the article: • <u>Spontaneous Trial Period</u> – First Phase; Individual managers initiated work improvement projects in different plants without each other's knowledge or coordination by the central administration. • <u>Socio-Technical Strategy Period</u> – Second Phase; Volvo took what it learned during the Spontaneous Trial Period and spread its knowledge throughout the Volvo system. • <u>The Match Project</u> – This OD program concentrated on organizational objectives which included improving communication about responsibilities, schedules, and objectives as well as providing new employees with good training. • <u>*Full Rulle*</u> – This OD program was a company-wide effort to create a common leadership philosophy and style. Among other things, it sought to empower and improve the skills of employees and team leaders while advocating for labor-management cooperation. • <u>*Dialog*</u> – This OD program emphasized the need to create dialogue to support change.
Applicability of results	This article did not inform EPA's learning rate estimate. It discusses management techniques related to managing the workforce and it does not estimate the relationship between cumulative output and cost.
Themes	Diffusion of knowledge gained through learning, Application of the learning curve

Dutton, J. M., & Thomas, A.

Article	**Treating progress functions as a managerial opportunity**
Publication	*The Academy of Management Review*, Vol. 9, No. 2, pp. 235–247
Date	1984
Industry examined	Secondary analysis of data from studies in a variety of industries, including electronics, machine tools, EDP system components, papermaking, aircraft, steel, apparel, and automobiles. The literature is drawn from industrial engineering, economics, and management.
Research question(s)	• Can future progress rates be predicted? • What factors cause progress? • How can the rate of improvement be managed?
Type of learning examined	Sources of variation in the learning rate
Data sources	More than 200 empirical and theoretical studies of progress functions in industrial engineering, economics, and management from 50 years of literature
Data size	Unspecified
Data years	Unspecified
Data adjustment	None
Methodology	Qualitative analysis of previous literature
Statistical methods used	The authors constructed a frequency distribution of progress ratios obtained from a sample of 108 studies of manufacturing processes in industries such as electronics, machine tools, EDP system components, papermaking, aircraft, steel, apparel, and automobiles to test the variability of progress rates. No industry-level experience curve studies or studies showing price declines were included.

<table>
<tr><td>Results</td><td>

The progress ratio, 81%–82%, has the highest frequency. Generally, reported progress ratios range from 55% to 108%.
The progress ratio is neither fixed nor automatic. It is often an outcome of managerial policy decisions regarding production, marketing, and joint decisions.
Not only do recorded progress rates vary across industries, processes, and products, they also differ for similar process and products. Progress rates have even varied widely for subsequent runs of the same product in the same plant.
In any given industry, firms’ progress functions, as well as progress rates, vary widely. This variation extends not only across firms at a given time, but also within firms over time.
From their analysis, the authors found that four main categories of factors caused progress:

Effects of technological change
Cumulative investments and improvements in capital equipment explain a significant part of the variation in progress rates in similar processes and facilities.
Horndal (labor learning) effects
Progress is brought about by direct and indirect labor learning.
Progress can be attributed to adaptation efforts by labor and technical personnel and to other autonomous cost-reducing effects of sustained production of a good.
Local industry and firm characteristics
The progress curve is affected by local operating system characteristics (e.g., the degree of mechanization, the ratio of assembly to machining, the length of cycle times, continuous vs. batch process).
Scale effects
Scale can contribute to progress effects, but how this occurs is not fully understood.
Findings regarding the effects of the rate of output on the progress curve remain mixed and contradictory.

The four causal factors (or combinations of them) explain observed progress in varying degrees.
Because most causal factors of progress functions cut across organizational subunit lines, intraorganizational relations may influence progress effects.

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<tr><td>Assessment</td><td>N/A</td></tr>
<tr><td>Conclusions</td><td>

Due to the variation in the frequency distribution, caution is needed in estimating future progress rates.
The progress principle is of limited use in a firm’s strategic planning because its underlying dynamics are not well understood.
To induce progress from variability (i.e., progress functions that are not subject to the same known sources of variation over space and time), managers need to document evidence for specific sources of progress variation accessible to the firm’s influence.
Progress in the form of continuous cost improvements may occur autonomously or be induced.
Managers who wish to use the progress curve need to identify and take advantage of static and dynamic opportunities (there are short-run and long-run dynamic

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</table>

	opportunities).
Future research	• An analysis that combines progress functions and organizational behavior variables to capture the interdependence among causes of progress, which cut across firms' hierarchical, subunit, and organization-environment boundaries
Other notes	Definitions of terms used in the article: • <u>The progress principle</u> – a firm can expect continuous improvement in its input-output productivity ratios as a consequence of a growing knowledge stock (or the cost input per unit declines at a uniform rate with cumulative production). • <u>Experience</u> – a means for firms gaining knowledge • <u>Progress</u> – a result of firms gaining knowledge • <u>Induced learning</u> o Requires investment, induction, or resources made available that are not present in the current operating situation o Affected by proximate causes • <u>Autonomous learning</u> o Automatic improvements that result from sustained production over long periods o Due to distant causes o More systematic and predictable given a set of system characteristics • <u>Exogenous learning</u> o Progress usually results from information and benefits acquired from external sources (e.g., suppliers, customers, competitors, and government). • <u>Endogenous learning</u> o Attributable to employee learning within a firm as manifested by technical changes, direct-labor learning, and smoothing production flow
Applicability of results	This study did not inform EPA's learning rate estimate because it is a secondary analysis of other studies related to learning by doing and it does not estimate any progress ratios based on original data.
Themes	Estimated learning rates, Sources of variation in learning rates

Epple, D., Argote, L., & Devadas, R.

Article	**Organizational learning curves: A method for investigating intra-plant transfer of knowledge acquired through learning by doing**
Publication	*Organization Science*, Vol. 2, No. 1, pp. 58–70 (Special Issue: Organizational Learning: Papers in Honor of (and by) James G. March)
Date	1991
Industry examined	North American truck plant producing a single vehicle

Research question(s)	• How can a conventional learning curve model be generalized to investigate factors responsible for the variations in organizational learning rates?
	• Investigate three aspects of knowledge transfers acquired from learning:
	  o Carry forward of knowledge when the plant makes the transition from 1-shift-a-day operation to two shifts per day
	  o Transfer across shifts after 2-shift-a-day operation is underway
	  o Transfer across time or the persistence of knowledge

Type of learning examined	Learning by doing; Knowledge transfer across shifts and across time; Knowledge depreciation, Location of knowledge
Data sources	• Data from an actual truck plant. Operated with one shift for several months, then switched to 2-shift operation. The plant is unionized. • Weekly data for a period of 19 weeks under 1-shift operation and 80 weeks under 2-shift operation
Data size	• Weekly data beginning at the start of production for a period of 19 weeks of operation with one shift and 80 weeks of operation with two shifts • Deleted five observations that were not representative of normal operating conditions from the sample
Data years	1980s, exact years not specified; 99 weeks of weekly data
Data adjustment	None
Methodology	Linear estimation; adjust the model to capture many aspects of learning; test the model as it is adjusted. The authors started with Eq. 5 to estimate the coefficient related to the progress ratio. (5) $ln\left(\frac{q_t}{l_t}\right) = a + \gamma ln(Q_{t-1}) + \epsilon_t$ Where, q_t – output during week *t* l_t – hours worked during week *t* Q_{t-1} – cumulative output at the end of the previous week γ – the coefficient related to the progress ratio; the percentage by which average labor hours per unit fall with a doubling of cumulative output The authors generalized Eq. 5 by capturing returns to increasing labor hours. (6) $ln(q_t) = a + \alpha \ln(l_t) + \gamma ln(Q_{t-1}) + \epsilon_t$ Because diminishing returns to labor could be more pronounced with an increase in

	hours per shift rather than with an increase in shifts per week, the authors modify Eq. 6 as follows: (7) $ln(q_t) = a + \alpha \ln(h_t) + \beta \ln(n_t) + \gamma ln(Q_{t-1}) + \epsilon_t$ Where, h_t – hours per shift n_t – shifts per week (Note, $l_t = h_t \times n_t$) The authors generalized Eq. 7 by capturing knowledge depreciation. (9) $ln(q_t) = a + \alpha \ln(h_t) + \beta \ln(n_t) + \gamma ln(\sum_{s=1}^{t-1} \lambda^{t-s-1} q_s) + \epsilon_t$ Where, λ – depreciation parameter (λ<1 implies a less than complete carry forward of knowledge to the next period) The authors generalized Eq. 9 by capturing the changing rate of learning as the knowledge stock grows. (10) $ln(q_t) = a + \alpha \ln(h_t) + \beta \ln(n_t) + \gamma ln(K_{t-1}) + \delta[ln(K_{t-1})]^2 + \epsilon_t$ Where, K_{t-1} – the knowledge stock The authors generalized Eq. 10 by capturing intra-plant transfers of knowledge (i.e., incomplete carry forward of knowledge and incomplete transfer across shifts). (12a) $ln\left(\frac{q_t}{2}\right) = a + \alpha ln(h_t) + \beta ln\left(\frac{n_t}{2}\right) + \gamma ln K_{t-1} + \delta(ln K_{t-1})^2 + \epsilon_t$ Where accumulated knowledge stock is: $$K_t = \lambda K_{t-1} + (1 + \theta)\left(\frac{q_t}{2}\right)$$ Where θ – amount of transfer (1 is a full transfer; less than 1 is an incomplete transfer, 0 is no transfer) The variables are halved to account for the special case in which the two shifts are treated symmetrically. This is necessary because the data are not disaggregated by shift.
Statistical methods used	• Regression with first-order autocorrelation of the residuals - Models 1–3 (Eqs. 5–7) • Maximum likelihood - Model 4 (Eq. 9)
Results	• Model 1 (Eq. 5) shows strong evidence of learning (learning parameter is 0.15 (Std. Error = 0.02). • Model 2 (Eq. 6) shows that diminishing returns to labor were not apparent. • Model 4 (Eq. 9) shows that knowledge acquired through learning depreciates. (Accounting for knowledge depreciation in the model changes the coefficient related to the progress ratio). • Model 5 (Eq. 10) shows that the rate of knowledge acquisition declines as the knowledge stock increases.

	• Model 6 (Eq. 12a) shows that learning by doing yields large productivity gains as production progresses and knowledge is accumulated, but that the rate of knowledge accumulation declines as the stock of knowledge grows.
	  o A 2.9 fold increase in output per week would have occurred between the first week and the same week 1 year later (a 190% growth in productivity). (Learning parameter was 1.5)
	  o 69% of knowledge acquired during the period of 1-shift-a-day operation is carried forward to the period of 2-shift-per-day operation.
	  o 56% of knowledge acquired on one shift is transferred to the other once both shifts are in operation.
	  o 60% of the knowledge stock at the beginning of a year would remain at the end of the year, if the stock were not replenished by continuing production. (However, not significantly different from the case with no depreciation)
	  o The more general formulation of the learning curve yields a very substantial improvement in the fit to the data.

Assessment	For Models 1 through 6, the authors conclude that the results "fit the data quite well, the algebraic signs of the coefficients are all as anticipated, and the magnitudes of the coefficients are all quite reasonable" (p. 67).
Conclusions	• A significant part of accumulated knowledge becomes embodied in the organization's technology. The results provide evidence, however, against the hypothesis that knowledge becomes completely embodied in the technology (e.g., tooling, programming, and assembly line layout and balancing) because the transfer of knowledge over time and across shifts was not complete despite using the same production facilities. • A substantial proportion of knowledge carried forward from 1-shift to 2-shift operation.
Future research	• Develop strategies for assessing the relative importance of training to develop individual skills, managerial skills, and/or a network of coordination and communication among members of the workforce. • Further illuminate the nature of the learning process. • Research the extent to which knowledge can be shared within production facilities.
Other notes	N/A
Applicability of results	This article did inform EPA's learning rate estimate because it is related to the mobile source sector, it uses primary data, and uses output as a dependent variable.
Themes	Generalizing the conventional learning curve, Factors responsible for organizational learning, Sources of variation in learning rates, Knowledge transfer, Knowledge depreciation, Location of knowledge within an organization (e.g., embedded in technology), Automotive industry

Epple, D., Argote, L., & Murphy, K.

Article	**An empirical investigation of the microstructure of knowledge acquisition and transfer through learning by doing**
Publication	*Operations Research*, Vol. 44, No. 1, pp. 77–86
Date	1996
Industry examined	Automotive assembly plant
Research question	• How does knowledge transfer across shifts? • Does knowledge acquired through learning by doing on one shift transfer to a second shift? If so, what amount? • Does the rate of knowledge acquisition differ by shift? • How much transfer of knowledge occurs across shifts when they are both in operation? • Does knowledge acquired through learning by doing accumulate or depreciate over time? • Is knowledge embedded in an organization's technology (e.g., tooling, programming, assembly line layout and balancing)?
Type of learning examined	Learning by doing; Knowledge transfer across shifts; Knowledge depreciation; Location of knowledge
Data sources	• Data from an actual automotive assembly plant • The plant operated with one shift for about 2 years, then switched to 2-shift operation. • The plant is unionized with about 1,000 direct labor employees working on a typical shift.
Data size	Daily data for each shift for 12 months prior to the introduction of 2-shift operation (244 observations) and 15 months afterwards (326 observations for Shift 1 and 329 observations for Shift 2): N=899.
Data years	Not specified; prior to 1996
Data adjustment	None
Methodology	Log-linear approach to allow for the use of linear estimation Production function: (1) $ln(q_{it}) = \beta_0 + \beta_H ln(H_{it}) + \beta_L ln(L_{it}) + \beta_K ln(K_{it-1}) + \beta_\tau t + \epsilon_{it}$ Where, q – number of vehicles produced H – total direct labor hours L – line hours of operation K – stock of knowledge *i* – shift; 0 is single-shift operation; 1 is Shift 1; 2 is Shift 2 *t* – date The model of knowledge acquisition, retention, and transfer (from Epple, Argote, & Devadas, 1991):

	During the period of 1-shift operation): (2) $K_{0t} = \begin{cases} 0 & \text{for } t = 0 \\ \lambda K_{0t-1} + q_{0t} & \text{for } 1 \leq t \leq S \end{cases}$ Eq. 2 states that knowledge at the end of any period is equal to production in that period plus λ% of the knowledge available at the end of the preceding period. During the period of 2-shift operation: (3) $K_{it} = \begin{cases} 0 & \text{for } t = S - 1 \text{ and } i, j = 1, 2, j \neq 1 \\ \lambda K_{it-1} + \mu_i q_{it} + \theta_i q_{jt} + \Delta C_{it} & \text{for } t = S, \ldots, T \text{ and } i, j = 1, 2, j \neq 1 \end{cases}$ (4) $\Delta C_{it} = \begin{cases} \emptyset_i K_{0S} & \text{for } t = S - 1 \\ \left(1 - \frac{\emptyset_i}{\rho_i}\right) \lambda \Delta C_{it-1} & \text{for } t = S + 1, \ldots, T \end{cases}$ Where, λ – parameter measuring forgetting (i.e., knowledge depreciation) μ – parameter measuring knowledge acquired per unit of production during the period of 2-shift operation θ – knowledge transfer parameter indicating how much knowledge is transferred between shifts Φ – proportion of knowledge carried to shift *i* at the date of transition from 1-shift operation to 2-shift operation ρ – fraction of knowledge ultimately carried forward from 1-shift operation to the period of 2-shift operation S – the last date of operating with one shift T – the last date for which data is available Eq. 3 states that Shift *i* retains λ% of the knowledge acquired through the end of the previous period; it acquires μ units of knowledge per unit of its own production, and it transfers θ. At date *t*, shift *i* carries forward an additional ΔC_{it}. Eq. 4 states that output at $\Phi_i K_{0S}$ units of knowledge from the period of 1-shift operation are carried forward immediately to shift *i* of 2-shift operation. If $\rho_i > \Phi_i$, then additional increments are carried forward in subsequent periods.
Statistical methods used	Maximum likelihood approach; Tobit estimation procedure is used because the dependent variable is truncated (i.e., maximum line speed, which determines the maximum number of vehicles that can be produced). Four versions of the model were estimated to sequentially add the impacts of knowledge carry-forward, knowledge acquired by vehicle by shift, and time. The fully estimated model's results are directionally as expected. Different versions were estimated to address questions with the results of the previous estimations.
Results	• All coefficients are statistically significant and in the correct direction. • The daily parameter measuring forgetting is .98; hence, the monthly rate of depreciation is approximately 67%. (There are 20 working days in a month; $.98^{20} = 0.67$)

Assessment	• All knowledge acquired during the period of 1-shift operation was carried forward to the period of 2-shift operation. o *Carrying the knowledge to the day shift occurred instantly, and carrying the knowledge to the night shift was slower, yet complete after 2 weeks of the 2-shift operation.* • Knowledge depreciates (.98, for a monthly rate of approximately 67%). Note there is also productivity growth associated with time, and this component does not depreciate. • The rate of knowledge acquisition per unit for 2-shift operation is about half as large as the rate for 1-shift operation. This could be due to the fact that there are less indirect labor hours (e.g., engineering and R&D) in the second shift.
Conclusions	• The authors developed "an intuitively plausible and appealing picture of the learning process" (p.84) and tested the model on actual data. • Every coefficient is of the predicted sign and falls within the predicted bounds. • Knowledge acquired during the period of 1-shift operation carried forward to both shifts of the 2-shift regime. • The rate of carry forward was somewhat slower for the second than the first shift, but was rapid in both cases. • The rapid and almost complete carry forward of knowledge from the first shift to the second when it was introduced, with only technology and structure being constant for both, suggests that knowledge acquired during the period of 1-shift operation was embedded in the organization's structure or technology. • The learning rate per unit of output during the 2-shift regime was roughly half that during the 1-shift regime. Most of the learning occurred on the first shift, and most of that knowledge was transferred to the second shift. Reduced managerial and industrial engineering attention on the second shift suggests why the reduced learning rate per unit of output on the second shift occurred.
Future research	N/A
Other notes	• The authors made a few adjustments to the model which did not affect the results. That is, in addition to removing the largest outliers, the authors squared the log of knowledge to allow for the possibility that depreciation is the result of decreases in the incremental benefits of knowledge. The coefficient of the squared knowledge variable was negligible in magnitude and statistically insignificant. • There is an interesting discussion on learning at the sector level that suggests there is no cross-industry learning and learning occurs on the level of the production facility. While the idea that organizations learn from each other has been explored (Levitt & March, 1988; Huber, 1999), the following authors note that cross-industry learning is difficult to measure: Zimmerman (1982); Joskow and Rose (1985); Darr, Argote, and Epple (in press); Argote, Beckman, and Epple (1990).
Applicability of results	This study did inform EPA's learning rate estimate because it is related to the mobile source sector, it uses primary data, and it uses output as a dependent variable.
Themes	Knowledge depreciation, Location of an organization's knowledge (e.g., embedded in technology), Automotive industry

Gopal, A., Goyal, M., Netessine, S., & Reindorp, M.

Article	**The impact of new product introduction in plant productivity in the North American automotive industry**
Publication	*Management Science*, Vol. 59, No. 10, pp. 2217–2236
Date	2013
Industry examined	North American automotive industry

Research question	What are the impacts of new product development on a plant's productivity?
	
	Five hypotheses are tested:
	• H1: Plants that are involved in the new product launch exhibit lower productivity than plants that are not.
	• H2: Plants that deploy product flexibility in the body shop show smaller declines in productivity from a product launch compared to plants that do not.
	  o If the number of platforms produced > the number of production lines, the plant is body-shop flexible.
	  o The higher the ratio, the more flexible the body shop.
	  o 13 of 84 plants were body-shop flexible.
	• H3: Plants with prior experience in manufacturing a different product – but on the same platform as the launch product – show smaller declines in productivity from a product launch.
	• H4: Plants with more experience at launching products in the past show smaller declines in productivity from a new product launch.
	• H5: Plants that have peers within the same firm with experience in launching new products show smaller declines in productivity from a new product launch.
	
	Two objectives:
	• Ascertain whether a plant hosting a launch suffers from a decline in productivity (H1).
	• Identify factors that can mitigate the loss in productivity (H2–5).
	
	Does learning persist over time?

Type of learning examined	This article does not directly focus on learning that results from production. It focuses on how past experiences can mitigate decreases in productivity resulting from product launches. Three measures of experience: • Platform experience: number of vehicles (which differ from the type of vehicle currently being launched) produced in the 3 previous years • Launch experience: number of launches at the plant in the 3 previous years • Firm experience: number of launches in the specific control set of plants in the 3 previous years
Data sources	• *Harbour Reports* (a survey of all North American automotive manufacturing plants) • Ward's Automotive (data such as monthly production at each plant and monthly sales)

Data size	Harbour Reports include:
	• 78 plants owned by four firms (i.e., former Daimler-Chrysler, Ford, GM, and Toyota)
	• 408 plant observations
	  o 88 product launches at 50 distinct plants (34 plants had more than one launch)
	  o Four observations were removed because the plants did not exist before the launch; hence, there were 84 total plant-year launch events (and 320 observations of non-launch events)

Data years	1999–2007
Data adjustment	Control variables: • Sales variance – changes in productivity due to demand variance • (Prior) Utilization – output ÷ annual capacity • Late model – plants with models near end of life-cycle • Product type – types of vehicles • Company – capture any firm-specific fixed effects • Year – capture any year-specific fixed effects

Methodology	• The method is similar to an event study (i.e., the authors estimate the loss of productivity at launch plants compared to non-launch plants.)
	• The dependent variable is productivity change (i.e., the relative change in productivity at each plant from the preceding year)
	  o A *positive* value reflects the percentage productivity *decline* during the launch.
	  o Average productivity change: 9.52% for launch plants; -5.24% for non-launch plants

Statistical methods used	H1: Two approaches
	• Series of matched sample methodologies:
	  o “obvious” managerial constraints
	  o propensity scoring methods,
	  o nearest-neighbor bias-corrected matching estimators
	  o nearest-neighbor matching estimators with trajectories
	• Instrumental variable approach; Probit model to estimate probability of being a launch site
	• Identify best match and compute mean productivity change for each group; do for single lag and trend
	• OLS regression; Heckman sample selection methodology
	
	H2–H5: OLS regression; Heckman sample selection methodology; panel data
	
	To assess if learning persists over time:
	• Re-estimate the OLS model of productivity by explicitly disaggregating these variables by year

Results	H1: All of the methods to assess impacts of product launch show a decrease in productivity. Range is 12.5% to 15.9% for matched samples. For regression, the estimated coefficient is 11.97% (treatment effects) and 14.84% (random effects)

	Findings related to mitigating increases in HPV: • H2: Product flexibility in the body shop: -10.82% • H3: Producing using the launch platform in the past: -2.057% • H4: Launching products in the past: -3.133% • H5: Firm experience in launches: No support Both methods (OLS and panel data) support these findings; panel data findings slightly lower (-7.38%, -1.953%, and -2.311%, respectively) With respect to persistence of learning over time, some forms of learning persist across 3 years (e.g., prior platform experience); others fade more quickly (prior launch event experience).
Assessment	N/A
Conclusions	Product launches cost money by reducing plant productivity by 12%–15% ($42–$53 million). One could reframe these results as showing that there is transfer from previous products to the new product. That is, when a new product is launched, it, not surprisingly, causes a downward blip in productivity of 12%–15% but much of the knowledge transfers to the new product. Steps can be taken to mitigate the decrease in productivity due to launches: plants with experience in manufacturing similar products, experience in product launches, and with flexible body shops do better. • Each unit of platform experience (100,000 launch platforms produced within the past 3 years) yields 2.1% savings in productivity. • Flexibility yields 10.8% savings in productivity. Implied savings of $15.5 million at an average plant from one standard deviation of improvement Knowledge acquired through production on the launch-platform is 'sticky,' while the knowledge acquired through launching products in the past tends to depreciate faster. Thus, formal efforts to internalize and ingrain the knowledge acquired through product launches can further increase the efficacy of launches.
Future research	• Re-do with a more detailed data set (e.g., monthly productivity data). Look at networks of plants. • Study supplier relationships. • Look at impacts of product architecture. • Look at different types of firms (e.g., those producing similar products, those which are geographically close) to see if launch experience is significant.
Other notes	Definitions of terms used in the article: Launch: introduction of an all-new vehicle or *major* product change (e.g., new sheet metal or new exterior on a vehicle)
Applicability of results	This study did not inform EPA's learning rate estimate because it does not estimate any progress ratios.
Themes	Length of knowledge persistence, Automotive industry

Lapré, M. A., & Nembhard, I. M.

Article	**Inside the organizational learning curve: Understanding the organizational learning process**
Publication	*Foundations and Trends in Technology, Information, and Operations Management*, Vol. 4, No. 1, pp. 1-103
Date	2010
Industry examined	Secondary analysis of studies from several disciplines, both manufacturing and services
Research question(s)	Why do significant differences in learning rates exist across organizations?
Type of learning examined	Organizational learning; Typology
Data sources	None
Data size	None
Data years	None
Data adjustment	None
Methodology	The authors gather previous research and assemble it into a systematically organized body of knowledge on organization learning.
Statistical methods used	None
Results	**Chapter 1: Introduction** Common elements in the definition of org. learning: • The focus must be on the org. level not the individual level. • Enhancing knowledge and understanding within the organization • The purpose is to facilitate changes in actions to produce better org. performance. • It is an ongoing process that occurs throughout an organization's lifetime. Levels of learning • Learning is an iterative, multi-level process in organizations. • Knowledge and practices move from the individual to groups and teams to org. levels. • Learning at the org. level shapes how individuals and groups act and what they learn. **Chapter 2: Organizational Learning Curves** Three ways to measure experience: • Cumulative volume • Calendar time elapsed since the start of operation • Maximum proven capacity to date Four ways to measure performance: (1) unit time, (2) unit cost, (3) quality, and (4) total factor productivity

Chapter 3: Behind the Learning Curve: Understanding Variation in Learning Rates
Frameworks for Understanding the Variation in Learning Curves:

- Levy (1965): Autonomous vs. Induced Learning
  - Identified three types of firm learning:
    - Planned/Induced learning – results from firms applying techniques designed to increase the rate of output (i.e., reduce production costs)
    - Random/Exogenous learning – results when a firm acquires information unexpectedly from its environment (e.g., suppliers, government/trade publications, competitors)
    - Autonomous learning – results from employees' on-the-job learning or training
- Dutton and Thomas (1984): Autonomous vs. Induced and Endogenous vs. Exogenous
  - Learning-type dimension
    - Induced learning – requires investment, induction, or resources that are not currently present
    - Autonomous learning – automatic improvements that result from sustained production
  - Origin dimension
    - Endogenous learning – employee learning within a firm
    - Exogenous learning – results from information and benefits acquired from external sources (e.g., suppliers, customers, competitors, and government)
- Bohn (1994): Inside the learning curve
  - Variation in learning rates may be due to organizations differing in:
    - The amount/nature of experience and deliberate learning activities (DLAs) and the ability to learn from them
    - The ability to translate learning into better org. knowledge
    - The ability to change behavior in response to better org. knowledge
    - The ability to obtain better org. performance as a result of changed behavior

Variation Derived from Experience:

- Each framework agrees that experience is a core mechanism for org. learning; although all experience is not the same. Scholars have focused on three attributes of experience:
  - Specialized vs. diversified experience
    - Emerging studies found that a good balance between specialized experience and widely diversified or generalized experience maximizes learning; there is a U-shape relationship between exposure to variety and performance (more variety is better, but only up to a point).
      - Specialization – one can get a deeper understanding of an area and easier transferability of knowledge, but repetition can lead to stagnation
      - Diversity – can stimulate new ideas and foster a more complex understanding, but it can be difficult to integrate and apply

	knowledge across experiences o Success vs failure experience ▪ Organizations respond differently to the experience of success/failure ▪ Org. learning can be facilitated by both success and failure. ▪ Kim et al. (2009) found that organizations must accumulate a certain amount of the same experience (success or failure) before org. performance will improve as a result of learning. ▪ Results are mixed on whether success or failure is more advantageous. ▪ Research indicates whether and how an organization responds to and learns from successes/failures depends on a variety of factors: (1) the nature of the success/failure, (2) the level of each experience/the presence of other experiences, (3) the level of aspiration, and (4) the context. o Individual vs. team vs. org. experience ▪ Each level of experience has been theorized to provide learning and performance benefits. • With increased cumulative individual experience comes individual proficiency through knowledge/skill development. • With cumulative team experience comes better coordination and teamwork as individuals learn who knows what, who is best at performing each task, and how to trust each other. • With cumulative org. experience, staff learn from the knowledge accumulated by others. ▪ Reagens et al. (2005) found that team and org. experience had a consistently positive relationship with performance while individual experience had a U-shape relationship with performance (i.e., at low levels, increases hurt performance, at high levels, increases improved performance) Variation Derived from Deliberate Learning: • Types and amount of DLAs (e.g., training sessions, experiments, and quality management programs) o Faster learners use more DLAs that generate know-how and know-why, and they focus on learn-how. • Contextual differences o The greatest positive impact occurs when all org. participants support deliberate learning, when the use of DLAs occurs across multiple locations with time for reflection and with the purpose of quality improvement. • Macro-factors o Task characteristics ▪ Org. theory suggests that the proportion of tacit-to-explicit knowledge in a task explains a significant percentage of the variation in improvement rates for organizations learning to perform the same task. o Org. characteristics ▪ Argote et al. (2003) classified factors into three categories; those that affect the motivation, ability, and opportunity to learn

Chapter 4: Relative Effectiveness of Experience vs. Deliberate Learning as Sources of Learning

The Path to Optimal Learning: Experience or Deliberate Learning?

- The relative effectiveness of DLAs and experience may depend on:
  - The Stage of Production
    - When organizations are early in production, deliberate learning benefits the organization more than experience.
    - The relative benefit changes as the production process matures.
  - The Stage of Knowledge
    - Research found that learning from experience is more effective when knowledge is under-developed, while deliberate learning is more effective when knowledge is well-developed.
  - Task Characteristics (Zollo & Winter, 2002)
    - Deliberative learning would benefit tasks with high economic importance; a larger scope, involving multiple groups/departments; low frequency; high heterogeneity; or a high degree of causal ambiguity

Chapter 5: Moving from Learning to Performance: Steps Inside the Learning Curve

- To improve performance, organizations must go through three steps "inside the learning curve"
  - Develop better org. knowledge
  - Step 1 motivates changes in behavior
  - Step 2 contributes to improved cost and quality performance

From Learning to Better Organizational Knowledge

- Lapré et al. (2000) and Choo et al. (2007) provide evidence that learning is associated with knowledge creation.
- However, not all learning leads to better org. knowledge and performance.

From Better Organizational Knowledge to Changed Behaviors

- Mukherjee et al. (1998) showed conceptual and operational learning altered improvement project teams' ability to change behavior.
- Tucker et al. (2007) showed that learning results in the ability to spur behavioral change and actual behavioral change.

From Changed Behavior to Organizational Performance

- Nembhard and Tucker (2010) found that learning activities can facilitate the interdisciplinary collaboration, which is needed for performance improvement over time. They offer three explanations: Interdisciplinary collaborators (1) make better decisions, (2) have improved coordination, and (3) are skilled at detecting and learning from errors.

Challenges to Advancing

- Organizations can experience difficulty progressing from learning to improved performance due to at least four sets of factors:

	o Psychological and sociological factors ▪ Low psychological safety in organizations stifles the willingness to engage in learning and discourages individuals from interpersonal risk-taking out of fear of negative consequences. ▪ Other psychological factors limit learning – e.g., aversion to change and failure. ▪ Sociological factors • Social pressure – conformity creates a bias towards the leader's perspective • Traditional conflict management strategies – tend to force the majority view on the other party • Competency traps – tend to under-react by making the flawed assumption that current routines are preferable to alternatives o Cognitive factors/Learning capacity ▪ An organization's capacity for learning is a function of its resource and absorptive capacity. ▪ Organizations with limited resource and/or absorptive capacity are likely to learn less at a slower pace. ▪ Knowledge depreciation/forgetting limits the knowledge stock of learning. • Rates vary across settings and depend on calculation methods. o Complexity ▪ Several complexities impede org. learning such as: • Detail complexity – the presence of too many variables makes it difficult to comprehend a problem in its entirety • Dynamic complexity – when distance and time make cause-and-effect difficult to establish • Incomplete technological knowledge – lack of understanding the effects of a process' input variables on output o Multi-level process ▪ Learning's effectiveness is susceptible to factors at multiple levels • Individual – their knowledge/experiences can facilitate or hinder learning • Group – interpersonal dynamics and group norms • Org. – organizational structure/design ▪ Four core challenges to moving to the next level: (1) role-constrained learning, (2) audience learning, (3) superstitious learning, and (4) learning under ambiguity
Assessment	N/A
Conclusions	• Evidence consistently documents the org. learning curve phenomenon. • Evidence shows there is variation in learning rates. • The accumulation of experience at all levels of the organization enhances the learning rate. • Not all experiences are equally beneficial (e.g., failures seem to accelerate learning more than success). • The benefit of any experience depends on other factors (e.g., the nature of experience, the level of other experiences, the aspirational level, and the context).

	• There is little consensus on whether experience or deliberate learning influence productivity more. • Knowledge learned from experience depreciates.
Future research	The authors provide suggestions for future research throughout the book. Below, we are including those suggestions that were summarized in Chapter 6, which was specifically devoted to future research. **Chapter 6: The Next Frontiers in Organizational Learning Curve Research** Knowledge Creation • At what stages of causal and control knowledge can an organization expect to make more than merely incremental improvements? • Do breakthrough improvements require balanced climbing of the stages? • What is the impact of climbing the stages of knowledge for primary variables vs secondary variables? Learning by Experimentation • What experimentation strategies allow an organization to climb the stages of knowledge faster? Development of the Learning Organization • How does an organization become skilled at creating, acquiring, and transferring knowledge, and at modifying its behavior to reflect new knowledge and insights? • Are teams and training sufficient to transform an organization into a learning organization? • Identify different underlying mechanisms that govern the development of building blocks (besides a supportive learning environment, the presence of learning processes and practices, and leader behavior that provides reinforcement of learning.) • How do organizations manage and store their knowledge? • How does an organization effectively use knowledge reservoirs for org. learning? • How does an organization sustain learning? Learning Curves for Other Measures of Organizational Performance • Study additional dimensions of operational performance (besides cost, quality, and lead-time) such as supply chain management and sustainable operations management • Will too much experience eventually be detrimental? • Is there a way to avoid the competency trap of focusing on exploitation at the expense of exploration? • What org. learning efforts can re-ignite improvement after experiencing a reversal in performance? • Can the reversal effect be avoided by accumulating related experience? • Study dependent variables such as customer satisfaction, customer retention, repeat purchase, customer loyalty, and lifetime value of the customer. Learning to Improve Multiple Measures of Performance • Study the learning efforts behind performance improvement paths. • Can operating experience and DLAs simultaneously drive improvement for multiple measures of org. performance, or do different performance measures require different learning variables? • How would learning effects differ across different pairs of performance measures?

	• What learning activities can prevent trade-offs between operating priorities? Longitudinal Data Envelopment Analysis: Competitive Learning • Which firms consistently perform on the efficient frontier? Which do not and why? • What types of experiences and DLAs foster competitive learning? • What learning activities can prevent a firm from falling off of the efficient frontier?
Other notes	N/A
Applicability to Results	While this book is a comprehensive review of the status of the learning curve field, this study did not inform EPA's learning rate estimate because it is a secondary analysis of other studies related to learning by doing and it does not estimate any progress ratios based on original data.
Themes	Specification of the learning curve, Sources of variation in learning rates, The learning process, Barriers to learning

Lee, J., Veloso, F. M., Hounshell, D. A., & Rubin, E. S.

Article	**Forcing technological change: A case of automobile emissions control technology development in the US**
Publication	*Technovation*, Vol. 30, No. 4, pp. 249–264
Date	2010
Industry examined	Automobile industry; automobile emission control technologies
Research question(s)	• How do firms manage and organize their R&D processes concerning automobile emissions control technologies amid the uncertainties resulting from the issuance of new regulations? • Did government actions, from merely threatening to impose regulations to the actual imposition of increasingly stringent ones, actually influence the innovative activities of automakers and their suppliers? • If so, where does the technology come from? • Who are the key contributors? • How does “learning” take place during the process of technological development under technology-forcing regulatory regimes?
Type of learning examined	Learning by doing
Data sources	• U.S. Patent and Trademark Office (USPTO) data set • Technical papers published by the Society of Automotive Engineers (SAE) special (SP) series publications • Cost data set for automobile emissions control devices compiled from two main sources: (1) the EPA (1990) and the California Air Resource Board (1996) • Interviews with industry experts involved in the development of automobile emissions control technology
Data size	• 2,253 automotive emissions control-related patents • 701 SAE technical papers
Data years	1970–1998
Data adjustment	• The authors generated the relevant patent set using the USPTO data set using abstract-based and class-based keyword searches. Duplicate or irrelevant patents were removed. • The authors generated the SAE technical paper data set by screening the relevancy of the articles. • The authors adjusted costs data to constant 2000 dollars.
Methodology	Combination of quantitative and qualitative methods (i.e., interviews with experts). *Inventive activities: Timing of technology introductions and patenting trend* • Mapped a series of the onset of automotive emissions control regulations and corresponding levels of stringencies for major pollutants against the introduction of critical new technologies • Contrasted time-series with the magnitudes of patenting activities with the same series of stringency levels for the major pollutants • Regressed the onset of technology-forcing regulations on the level of innovation

	Sources and the locus of innovation • Associated entities developing patents and technical papers *Knowledge management and task uncertainty* • The authors classified patents as either architectural or component innovation and defined three periods of either certainty or uncertainty between 1970 and 1998. The authors then estimated the share of patents held by automakers and suppliers by innovation type and period of certainty/uncertainty. • Performed a Probit estimation using component innovation as the dependent variable *Learning by doing* • The authors graphed the estimated average cost of catalysts per vehicle over the period of 1972–1994. • The authors regressed the cumulative number of emission control devices installed on the normalized cost of emission control devices. • Estimated the progress ratio for learning related to non-catalyst components
Statistical methods used	The authors developed a statistical model based on the Probit estimation approach using component innovation as the dependent variable.
Results	*Inventive activities: Timing of technology introductions and patenting trend* • The authors found that the automotive industry launched new emissions control technologies whenever increasingly more stringent regulatory standards phased-in. The timing of their findings did not always match regulation changes. • An increase in stringency appears to lead to an increase in patenting activity. • The authors found a positive and significant relationship between the onset of technology-forcing regulations and the level of innovation. Again, findings did not always match regulation changes. • Automakers and suppliers were the major players in the development of automobile emissions technologies, accounting for more than 93% of patents and 73% of technical papers. *Sources and the locus of innovation* • Suppliers were the main locus of innovation prior to 1975 (before the introduction of the first-generation catalytic converter). Automakers became the principal locus of innovation thereafter, which implies they became active as "system integrators" in product development. They possessed knowledge of all of the system's aspects. *Knowledge management and task uncertainty* • Automakers and suppliers dominated architectural and component innovation, respectively, throughout each period. • Component innovations by automakers and architectural innovations by component suppliers increased with the imposition of more stringent regulatory standards during the 1970s and 1990s, both periods of uncertainty. This suggests that suppliers and automakers tend to engage in architectural and component innovation, respectively, amid task uncertainties.

	Learning by doing • The authors believe the overall cost of emission control devices did not change after 1984 because potential cost reductions due to learning could have been cancelled out by the increases in the cost of precious metal catalysts. However, precious metal costs varied significantly during this period. • The authors estimated that reductions in the cost of non-catalyst components due to learning took place with a progress ratio of 0.93 between 1984 and 1990. These components were not affected by fluctuations in the price of precious metals. This finding was based upon seven data points and the authors suggest this is a rough estimate of progress.
Assessment	• The rough estimate of the progress ratio of 0.93 is somewhat slower than the average progress ratio of 0.81 found in manufacturing by Dutton and Thomas, 1984. o Much of the innovation during this period was due to catalyst formulations, which were not taken into account in the analysis because of the large variation in precious metal costs. o The estimate is based on a very limited number of points (seven points). o While technology -forcing regulations occurred during the 1970s and 1980s, by the mid-1990s, regulatory agencies began working with manufacturers to develop new emission standards that could be accomplished by industry and represented a step reduction in emissions.
Conclusions	• High regulatory standards under the technology-forcing regulation played an important role in forcing technological innovations and determining subsequent direction of technological change. This method has now changed to a more collaborative approach with industry. • Component suppliers were important sources of innovation in the 1970s, but over the course of technological evolution, automakers gradually emerged as the locus of innovation. • Firms strategically manage architectural and component knowledge in the presence of uncertainties about their technological capacity to meet new auto emissions control standards. • The rough progress ratio estimated in this work was based upon limited data and did not take into account catalyst formulation changes which were the main factor in reducing emissions to meet new standards. • The authors claim great period of uncertainty when new regulations were passed. EPA and other regulatory agencies develop regulatory impact analyses while formulating regulations, which provide information on technologies to meet standards and provide expected costs.
Future research	• Test whether there is a relationship between stringent regulatory pressures and the competitiveness of regulated firms by incorporating international trade dimensions with regulatory pressure and patenting activities of regulated firms. • Evaluate innovative capabilities of supplier networks. • Understanding the structural relationships, changes in the key players, and their linkages with exogenous environmental events should provide a clearer picture of the forces that drive technological evolution and the success of government regulations in stimulating innovation.
Other notes	Definitions of terms used in the article:

	• Technology-forcing regulations – regulations that mandate firms to meet performance standards that go beyond the existing technical capabilities of the industry or to adopt specific technologies that have not been fully developed (Jaffe et al., 2002) • System integrators – firms that integrate and coordinate the internally developed and externally produced works of suppliers (Robertson & Langlois, 1995; Brusoni et al., 2001) • Architectural innovation – embodies knowledge on how components are linked • Component innovation – embodies knowledge on components • Period of uncertainty – (1970–1981; 1990–1998) during the presence of regulatory pressure • Period of certainty – (1982–1989) during the absence of regulatory pressure
Applicability of results	This study did not inform EPA's learning rate estimate because its data on learning were limited. The progress ratio was estimated using only seven data points and the dependent variable used to estimate the progress ratio was not described in the article. There is also a concern that the number of patents and papers is not a valid measure for learning and is more a measure of technological change. In addition, the estimation of the progress ratio did not take into account the interaction between regulations, regulatory intent, and politics. For these reasons, the progress ratio calculated here may not be a good indicator of learning.
Themes	Automobile industry, Regulation's role in learning

Levitt, S. D., List, J. A., & Syverson, C.

Article	**Toward an understanding of learning by doing: Evidence from an automobile assembly plant**
Publication	*Journal of Political Economy*, Vol. 121, No. 4, pp. 643–681
Date	2013
Industry examined	Automobile (assembly plant of an auto producer)
Research question(s)	• What is the rate of learning by doing? • What are the processes by which improvements occur?
Type of learning examined	Learning by doing; Knowledge transfer or spillover; Location of knowledge
Data sources	• Production data from an assembly plant of a major auto producer collected by Factory Information System (FIS) proprietary software • Daily records of absent employees from an administrative database • Warranty claims made on the cars produced
Data size	The data cover the production of 200,000 cars (include three model variants).
Data years	• One year, which is not specified for proprietary reasons. The August to December period is labeled Year 1. The January to July period is labeled Year 2. • Model 2 was introduced 17 weeks after the start of the analysis period. Model 3 was introduced 13 weeks after the start of Model 2.
Data adjustment	• The authors removed the small number of prototype vehicles produced at the start of the analysis period from the sample. These cars were used for training and to find major difficulties in the production process; therefore, they featured high defect rates. • For consistency, when describing the introduction dates of Models 2 and 3, the authors impose a threshold of 100 cars per week being produced for the cars' production data to be included in the sample. • The authors segmented the production process by benchmark operations. They apportion the car to a production week by segment. The sum of complete and partial cars produced within a period equals the number of cars produced per period. • The authors exclude any weekend operations.
Methodology	To estimate overall learning patterns: • Use the basic specification: $$\ln(S_t) = \ln(A) + \beta \ln(E_t)$$ Where, S_t – productivity at time *t* (average defect rate) E_t – production experience up to that point (i.e., cumulative production) β – learning parameter • Add a time trend to the basic specification. • Replace the time trend with the following experience term to allow for organizational forgetting: $$E_t = \delta(E_{t-1} + q_{t-1})$$

Where,

δ – the retention parameter

E_{t-1} – experience at the start of the prior period

q_{t-1} – production in the prior period

Supplementary evidence from quality audits:

- Compare FIS data to an independent production defect measure (the quality audits on randomly selected cars) and data on warranty claims.

To explore the mechanisms driving learning by doing:

Adding a Second Shift:

- Estimate shift-specific learning rates, where the logged average error rates on a shift are regressed on the log of cumulative production from that shift.
- Estimate ramp-up spillovers by including a dummy variable for the second-shift ramp-up period to the first-shift-specific learning regression.

Introducing Additional Product Variants:

- Estimate model-specific learning by doing rates by regressing the logged average error rates on a shift on experience (cumulative production of the specific model variant).

To test for station-level patterns:

Distribution of defects:

- Measure the skewness of defect rates across production stations and test for intertemporal changes in this skewness.

Persistence:

- Investigate the correlation of station-level error rates across shifts by grouping all stations by their quintile within the shift-specific defect rate distribution during a particular week and compare a given station's quintiles across the first and second shifts that week.

To test defect spillovers across cars:

- Regress the defect count of a given car on the defect counts for each of the 25 cars that preceded it along the assembly line. Control for day fixed effects. The model is done separately for three different production periods (i.e., early in the model year, middle of the year, and year's end)

To test absences and the role of worker-embodied learning by doing:

- Disaggregate production and absentee data to test if absenteeism and defect rates are correlated.
- Use the "forgetting specification" and allow the rate at which the knowledge stock depreciates to vary with the fraction of workers who are absent.
- Compute defect and absences by department-shift-day cells and combine the data to create a panel. Regress the log of defect rates on the log of employee absences, controlling for department-shift and day fixed effects.

	To test implications for warranty payments: • Regress warranty payments for a particular car on the number of defects that occurred during assembly. Include week-of-production fixed effects.
Statistical methods used	Regression with fixed effects
Results	To test overall learning patterns: • Using the basic model specification, the estimated learning rate was -0.284 (s.e.=0.008) and -0.301 (s.e.=0.006) using weekly and daily data, respectively; a doubling of cumulative output led defect rates to fall by 17.9% ($2^{-0.284}$=0.821) and 18.8% ($2^{-0.301}$=0.812) using weekly and daily data, respectively. • Adding the time trend did not change the estimated coefficients much. • When allowing for forgetting, the estimated retention rate was .965 (weekly data) and .985 (daily data, which was .927 when compounded over a 5-day production week). Approximately 3% to 7% of the plant's production experience stock was lost every week. To explore the driving mechanisms of learning by doing: *Adding a Second Shift:* • The estimated learning rates were smaller for the second shift than the first shift. Using weekly data, the estimated learning rate was -0.318 (s.e.=0.011) and -0.148 (s.e.=0.010) for the first and second shift, respectively. A doubling of cumulative output led defect rates to fall by 19.8% ($2^{-0.318}$=0.802) and 9.7% ($2^{-0.148}$=0.903) for the first and second shift, respectively. • The estimated coefficient on second shift ramp-up dummy variable was 0.151 (s.e.=0.058); indicating that first-shift defects were roughly 15% higher during the weeks the second shift was ramping up. *Introducing Additional Product Variants:* • The estimated learning rate was -0.331, -0.188, and -0.214 using weekly data for Model 1, 2, and 3, respectively. (A doubling of cumulative output led defect rates to fall by 20.5%, 12.2%, and 13.8%, respectively). The estimated learning rate was -0.355, -0.204, and -0.236 using daily data for Model 1, 2, and 3, respectively. (A doubling of cumulative output led defect rates to fall by 21.8%, 13.1%, and 15.1%, respectively). • The ramp ups for Model 2 and 3 led to an 8% and 30% increase in defects rates in Model 1 production, respectively (using daily or weekly data). To test station-level patterns: *Distribution of defects:* • Defect rates were highly skewed across stations. • All quantiles featured considerable reductions in relative defects early in the production period that decelerated over time. *Persistence:* • Defect rates at the station level were quite persistent. Still, the share of defects accounted for by top-quintile stations shrunk between the first and second period.

	• The persistence of error rates was evident from the transition matrix. Persistence was greatest at the very top and bottom of the distribution. • The correlation across shifts indicated that defect rates were persistent across shifts within a week. Again, the persistence was greatest for stations at the distribution's tails. To test defect spillovers across cars: • Spillovers clearly existed as defects on one car raised the likelihood of defects on the cars that came later in line. Defects on one car had statistically significant spillovers on at least the next 15 cars. • The magnitude of the spillovers fell as the distance between cars grew. • The economic size of these spillovers was nontrivial. To test absences and the role of worker-embodied learning by doing: • The estimated coefficient was 0.156 (s.e.=0.029), which implied a one-standard deviation increase in absences raises defect rates by about 1/7th of a standard deviation. To test implications for warranty payments: • There was a positive relationship between defects on a car and the amount of warranty payments the company made on it.
Assessment	To test overall learning patterns: • The daily and weekly specifications fit the data very well (high R^2 values). • The results with the time trend suggested quality improvement is related to production activity rather than to the passage of time. • Explicitly modeling forgetting does not substantially improve the ability of the model to fit the data relative to controlling for a time trend. • Evidence from independent quality control audits supports the authors' findings. To explore the driving mechanisms of learning by doing: *Adding a second shift:* • The estimated learning rate was significant for the first and second shifts using weekly data, but significant for only the first shift using daily data. • The patterns indicate that the efficiency and quality gains from the first period seem to be fully incorporated into second shift production immediately, despite having new workers. This suggests learning is embodied in the broader organization rather than in human capital. • The estimated coefficient on the second shift ramp-up variable was only significant using daily data. *Introducing Additional Product Variants:* • The estimated learning rate for Model 1 was similar to those found in the overall sample. The estimated rates for Models 2 and 3 were smaller. • The ramp up periods of subsequent models had a significant relationship with Model 1's defect rates but not Model 2's. This may be because solving problems that arise as Model 3's production begins detracts more resources from production of the most similar model, Model 1.

	• Knowledge stocks are not accumulated simply by workers producing any type of car. Learning depends not only on workers becoming acclimated to working together, but also on the similarity of the products being produced. Workers who have acquired experience producing one model cannot fully transfer the knowledge to the production of other models. This also suggests learned knowledge is not simply contained in human capital, but may be embodied in physical or organizational capital. To test station-level patterns: *Distribution of defects:* • Aggregate learning by doing reflects a proportional tightening of the entire station-level defect rate distribution, with all quantiles experiencing similar percentage declines in defect rates. • The results further indicate that an important component of learned production knowledge appears to be tied to the particular capital of the station, the organizational capital managing that station across shifts, or temporal fluctuations in the quality of parts being used as inputs. To test defect spillovers across cars: • It did not appear that a decrease in spillover effects over time explained the observed learning by doing patterns.
Conclusions	• Learning by doing is an important factor in the production process, particularly for the first few months of production after the initial ramp up. • Efficiency/quality gains seem to be immediately fully incorporated into the second-shift production, despite having completely new workers. • Introducing a new model variant into production causes productivity setbacks for those already in production. • The distribution of defect rates across the assembly processes is highly skewed. Station-specific defect rates persist over time and across shifts. • Defects spill over to the cars following on the assembly line (albeit at a declining magnitude). These effects do not decline over the year. • Worker absenteeism is related to defect rates, both directly and through the rate at which acquired learning-by-doing knowledge is retained. But the impact is economically small. • Defects per vehicle are related to warranty payouts by the firm. • Several findings suggest that productivity gains from learning are embodied in the broader organization rather being retained within the human capital of workers (supports the findings by Epple et al. (1996)).
Future research	Extend their research to other production operations.
Other notes	Definitions of terms used in the article: • <u>Ramp-up period</u> – the first 3 weeks of second-shift production, the time it took second-shift output to rise to the level of the first. • <u>Department</u> – a major portion of an assembly line's operations
Applicability of results	This study did inform EPA's learning rate estimate because it is related to the mobile source sector, uses primary data, and estimates the progress ratio based on average defects.

Themes	Estimation of learning rate, Determinants of learning by doing, Location of knowledge (e.g., embedded in technology)

Macher, J. T., & Mowery, D. C.

Article	**"Managing" learning by doing: An empirical study in semiconductor manufacturing**
Publication	*The Journal of Product Innovation Management*, Vol. 20, No. 5, pp. 391–410
Date	2003
Industry examined	Semiconductor industry, wafers of silicon
Research question(s)	• How does semiconductor manufacturers' use of teams for problem solving and intrafirm knowledge transfer influence performance? • How does the level of internal adoption of information technology (IT) influence performance? • How does more extensive and effective workflow and production scheduling systems influence performance?
Type of learning examined	Organizational-based learning by doing; Problem solving for production improvement; Location of knowledge
Data sources	Competitive Semiconductor Manufacturing Program
Data size	Data from 36 wafer fabrication facilities of U.S., European, Japanese, Korean, and Taiwanese semiconductor firms operating domestically and offshore
Data years	Multiple years (not specified); some firms have only 2 years of data
Data adjustment	• The wafer size variable was normalized to the industry standard. • Unequal weights were assigned to the *Materials Handling* variable to reflect that interbay materials handling automation is more complex and potentially more valuable to performance improvement. • Conveyor systems receive a higher weight because industry experts considered them to be more important than systems that load/unload production lots. • The variable, *Cycle Time per Layer*, was normalized according to the number of mask layers required by the device to not penalize product types with larger areas. • The variable, *Cumulative Volume*, is scaled to represent units of 1,000 wafer starts.
Methodology	The authors estimated the following equation: (10) $P_t = \gamma + e - [\beta_1 \cdot CV_t + HRP \cdot (\alpha_1 + \alpha_2 \cdot CV_t) + OP \cdot (\alpha_3 + \alpha_4 \cdot CV_t)] \cdot [P_0 - \gamma - (\beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML)] + \beta_2 LW + \beta_3 WS + \beta_4 CR + \beta_5 ML$ Where, P_t – defect density or cycle time parameter CV_t – cumulative volume; the sum of wafer starts from the initial observation to the current period (scaled to represent units of 1,000 wafer starts) HRP – the knowledge gained by implementing a particular human resource (HR) practice in the fab. These practices include: • Team Diversity – the degree to which both direct (i.e., operators and technicians) and indirect (i.e., engineers and supervisors) personnel are involved in problem-solving activities within the manufacturing facility • Team Number – measures the diversity of problem-solving team types

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operating in the facility

Colocation – measures whether manufacturing engineers are transferred to development and/or development engineers are transferred to manufacturing

OP – the knowledge gained by implementing a particular organizational practice in the fab. These practices include:

Material Handling – the extent of use of automated material handling in critical functions
Information Handling – the extent and use of automated information handling
Database Analysis – the extent of use of integrated database analysis of production performance and problem solving
Scheduling – the extent of use of production scheduling systems

Static Variables
LW – linewidth of the manufacturing process; a measure of technological sophistication
WS – normalized dimension of wafers manufactured
CR – the maximum clean room grade that exists in the fab; a measure of the number of particles per cubic foot in the fabrication facility
ML – number of mask layers used in the process; a proxy for the total number of steps in the process
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<tr>
<td>Statistical methods used</td>
<td>All models are estimated using a nonlinear maximum likelihood estimator using a first-order (AR1) correction for serial correlation. Fixed effects for each manufacturing facility are included in the estimation.</td>
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<td>Results</td>
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Using Cycle Time as the dependent variable; examines the effect on the speed of production (each model also includes the static variables):

Model 1 (CV) – As production increases, cycle time performance improves.
Model 2 (CV, Team Diversity, Team Number, Colocation, and their respective interaction terms)

Cumulative volume shows a positive and significant relationship with cycle time performance.
Team Diversity, Team Number, and Colocation appear to have a significant direct effect on cycle time performance. They initially shift the cycle time learning curve up, implying some cycle time penalty associated with their use.
Team Number and Colocation appear to have a significant indirect effect on cycle time performance. Their use accelerates performance in the face of new processes.

Model 3 (CV, Material Handling, Information Handling, Data Analysis, Scheduling, and their respective interaction terms)

Material Handling, Information Handling, Data Analysis, and Scheduling appear to have a significant direct effect on cycle time performance.

Material Handling shifts the cycle time learning curve down, initially improving cycle time.
Information Handling, Data Analysis, and Scheduling initially shift the cycle time learning curve up, implying some cycle time penalty associated with their use.

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	- *Material Handling, Information Handling*, *Data Analysis*, and *Scheduling* appear to have a significant indirect effect on cycle time performance.
	  - *Material Handling* produces slow rates of cycle time improvement as production volumes grow.
	  - *Information Handling*, *Data Analysis*, and *Scheduling* increase the rate of cycle time improvement as production volumes grow.
	• Model 4 (combines HR and technological practices)
	  - All of the HR and technological practice variables appear to have a significant direct effect on cycle time performance.
	    - *Team Diversity* and *Material Handling* initially shift the cycle time learning curve down, improving cycle time.
	    - *Team Number*, *Colocation*, *Information Handling*, *Data Analysis*, and *Scheduling* initially shift the cycle time learning curve up, implying some cycle time penalty associated with their use.
	  - *Colocation*, *Material Handling, and Information Handling* appear to have a significant indirect effect on cycle time performance.
	    - *Material Handling* produces slow rates of cycle time improvement as production volumes grow.
	    - *Information Handling*, *Data Analysis*, and *Scheduling* increase the rate of cycle time improvement as production volumes grow.
	
	Using *Die Yield* (Defect Density) as the dependent variable; examines the effect on the rate of learning (each model also includes the static variables):
	• Model 1 (*CV*) – Yield performance improves as cumulative volume increases.
	• Model 2 (*CV*, *Team Diversity*, *Team Number*, *Colocation*, and their respective interaction terms)
	  - Cumulative volume shows a positive and significant relationship with cycle time performance.
	  - *Team Number* and *Colocation* appear to have a significant direct effect on yield performance. They initially shift the yield improvement learning curve up, implying some yield penalty associated with their use.
	  - *Team Number* and *Colocation* appear to have a significant indirect effect on yield performance. Their use accelerates performance in the face of new processes.
	• Model 3 (*CV*, *Material Handling*, *Information Handling*, *Data Analysis*, *Scheduling*, and their respective interaction terms)
	  - *Material Handling, Information Handling*, *Data Analysis*, and *Scheduling* appear to have a significant direct effect on yield performance. They initially shift the yield improvement learning curve up, implying some yield penalty associated with their use.
	  - *Material Handling* and *Information Handling* appear to have a significant indirect effect on yield performance.
	    - *Material Handling* produces slow rates of yield improvement as production volumes grow.
	    - *Information Handling* accelerates performance in the face of new processes.
	• Model 4 (combines HR and technological practices) – *Colocation* and *Information*

	Handling are still significant. o *Team Number*, *Colocation, Material Handling, Information Handling*, and *Data Analysis* appear to have a significant direct effect on yield performance. They initially shift the yield learning curve up, implying some yield penalty associated with their use. o *Material Handling and Information Handling* appear to have a significant indirect effect on yield performance. ▪ *Material Handling* produces slow rates of yield improvement as production volumes grow. ▪ *Information Handling* accelerates performance in the face of new processes.
Assessment	• Each successive model is a statistically significant improvement in comparison to the initial model and produces largely consistent results. • The authors found the lack of influence of an integrated data analysis capability on yield improvement surprising given how important data analysis is viewed in yield management. The authors stated it may reflect that the levels of investment in this type of IT are less important than the details of its organization and deployment within the fab, aspects of IT investment that their measures captured imperfectly. • The authors were not surprised that automated scheduling systems of yield lacked influence because production scheduling affects production volumes and queues, which are more important for cycle time than yield improvement.
Conclusions	• The results obtained generally show similar effects from the implementation for HR and organizational practices on yield and cycle time performance. • The introduction of several of the practices initially have negative influence on manufacturing performance at low production volumes, but tend to increase the rate of improvement as production volumes expand. • Manufacturers that implement more types of problem-solving teams and policies that collocate production and development engineers and other key personnel appear to learn faster by making better use of tacit knowledge typically “locked up” within individual engineers or operators. • Firms with superior information handling automation and data analysis capabilities can improve yield or cycle time faster. These practices support higher levels of codification of otherwise tacit knowledge, which facilitates internal dissemination and accelerates firm-wide learning. • There is little or no evidence of significant benefits from other practices, nor do these activities affect all dimensions of performance equally.
Future research	N/A
Other notes	Definitions of terms used in the article: • <u>Die yield</u> – the proportion of die on a successfully processed wafer that pass functionality tests (measure of quality) • <u>Cycle time</u> – the time required to manufacture a semiconductor device (shorter cycle times allow plants to boost output or adjust more quickly to changes)
Applicability of results	This study did not inform EPA’s learning rate estimate because it does not use the power form to estimate learning; hence, progress ratios cannot be estimated using their results.

Themes	Determinants of learning, Location of knowledge (e.g., embedded in technology)

Nykvist, B. & Nilsson, M.

Article	**Rapidly falling costs of battery packs for electric vehicles**
Publication	Nature Climate Change
Date	2015
Industry examined	Battery electric vehicles (BEVs)
Research question(s)	What are the current and predicted costs of battery packs?
Type of learning examined	Learning in general; Forecasting costs
Data sources	The authors specify that the cost estimates "are from peer reviewed papers in international scientific journals; the most cited grey literature, including estimates by agencies, consultancy and industry analysts; news items of individual accounts from industry representatives and experts; and finally, some further novel estimates for leading BEV manufacturers" (p. 329).
Data size	The authors collected 85 cost estimates to be assessed for historical costs and 37 for future forecast costs.
Data years	2007–2014
Data adjustment	• The authors collected data and eliminated cross referrals and duplicative data points. They also excluded data that did not specify the method used. • For all data, costs ranges (if given) were converted to the arithmetic mean of the highest and lowest data points in the range. • Historical costs were inflation adjusted to US$2014 using data from the Bureau of Labor Statistics. • Currencies were converted using historical exchange rates from the US Federal Reserve. • Cumulative battery pack volumes were assessed by combining several sources in press releases for car manufacturers, data provided by actors following the industry, and data found in individual reports.
Methodology	• The authors performed a secondary analysis of over 80 estimates reported by other analyses between 2007 and 2014 to systematically trace the cost of Li-ion battery packs for BEV manufacturers. • The authors estimated the annual percent change in average costs between 2007 and 2014. • Learning rates were estimated by regression of log cost data on log cumulative output data using four data points modelled from this paper for 2011–2014 separately for industry as a whole, the market-leading manufacturers, and the net of both groups (excluding market leaders).
Statistical methods used	• Data were fitted with log regression and 95% confidence intervals, derived with a two-tailed *t*-test
Results	• Average costs for the industry as a whole declined by 14% annually and average costs for market-leading manufacturers declined by 8% annually over 2007 to 2014. • The estimated cost range in 2014 was $410/kWh and $300/kWh for industry and market-leading manufacturers, respectively.

	• The estimated learning rate was 9% for industry as a whole and 6% for market-leading actors. This implies the cost reduction following a cumulative doubling of production falls between 6% and 9%. • Costs in 2014 were probably already below average projected costs for 2020. • The cost estimates for the whole industry and market-leading cost manufacturers are estimated to converge in 2017–2018 at around $230/kWh.
Assessment	• All estimated declines in costs are significant. • The learning rate is in line with earlier studies on vehicle battery technology. • Cost data contained too much uncertainty to estimate learning rates directly. Modeled data from this paper was used instead, which gave highly significant results, but the underlying uncertainty in cost data must be taken into account when interpreting the results. • All of the results come with large uncertainties. • Sparse data makes statistical testing difficult. Learning rates were initially calculated by regressing log cost data and log cumulative capacity data; however, because the cost data's uncertainty was too high (i.e., the R^2-value was less than 0.1), the authors used modelled data from this paper, which consisted of only four data points, for the period 2011-2014. • The estimated current cost range in 2014 is two to four times lower than suggested in many recent peer-reviewed papers. • Industry may have incentive to overestimate costs to avoid revealing actual costs or conversely, that they subsidize battery packs to gain market shares. • The price range is widened as cost estimates are based on many cell chemistry varieties. • The estimated cost when industry and market-leading manufacturers converge ($230/kWh) is lower than estimates in peer-review literature, but on par with other estimates (McKinsey Quarterly, 2012).
Conclusions	• The literature reveals that costs of battery packs are decreasing, but with large uncertainties on past, current, and future costs of the dominating Li-ion technology. • Industry-wide cost estimates declined approximately 14% annually between 2007 and 2014. To some degree, this represents a correction of earlier, overestimated costs. • The costs of battery packs used by BEV manufacturers are lower and declined by 8% annually between 2007 and 2014. This decline likely represents the probable future cost improvement for Li-ion battery packs in BEVs. • The learning rate is 6% (for market-leading actors) and 9% (industry wide).
Future research	Future research efforts modeling scenarios for energy and transport transitions need to take these lower cost estimates into account.
Other notes	Possible explanations for the steep decline in industry-wide cost estimates: • The inclusion of data on market-leading actors • Cumulative global sales of BEVs are doubling annually, and learning rates for the constituent Li-ion cells have been estimated to be 16%–17% (Gerssen-Gondelack & Faaij, 2012). • Improvements made to input material cost and economies of scale • The period since 2007 represents the earliest stage of sales growth for BEVs. The estimates thus reflect a wide range of Li-ion battery variants at initially low

	production volumes as well as necessarily immature battery pack production techniques among BEV manufacturers. A rapidly developing and restructuring industry in its early phase could yield high learning rates at pack level.
Applicability of results	This study did not inform EPA's learning rate estimate because the study used secondary data and estimates were based on only four data points.
Themes	Estimating learning rates, Use of learning curves in forecasting

Rubin, E. S., Taylor, M. R., Yeh, S., & Hounshell, D. A.

Article	**Learning curves for environmental technology and their importance for climate policy analysis**
Publication	*Energy*, Vol. 29, No. 9, pp. 1551–1559
Date	2004
Industry examined	Electric power plants; flue gas desulfurization (FGD) and selective catalytic reduction (SCR) systems to control SO_2 and NO_x
Research question(s)	• How did the deployment and cost of these environmental technologies change over time? • How were these changes and technological innovations related to government actions and policies?
Type of learning examined	Learning generally
Data sources	Data from a 2001 PhD thesis by Taylor, based on a series of studies performed by the same organizations over a period of years using a consistent set of design premises.
Data size	Data size not provided
Data years	Data years not specified, although results are provided for 5 data years for each system (i.e., FGD systems: 1976, 1980, 1982, 1990, and 1995; SCR systems: 1983, 1989, 1993, 1995, and 1996)
Data adjustment	Costs are adjusted to a common basis for a standardized 500 MW power plant burning 3.5% S coal with wet limestone FGD systems achieving 90% SO_2 removal.
Methodology	Regress cost on cumulative production using the following functional form; log-linear format to allow linear regression. Learning curve: $y_i = ax_i^{-b}$ Where, y – cost to produce a unit x – cumulative production learning rate = $1-2^{-b}$ progress ratio = 2^{-b} In this approach, cumulative production or capacity is a surrogate for total accumulated knowledge gained from many different activities whose individual contributions cannot be readily discerned or modeled. The model includes both benefits from "learning by doing" and R&D investments that produce new knowledge and new generations of technology. The authors asserted that it would be ideal to distinguish R&D impacts, but data limitations prevent this. The model also precludes the impacts of government regulations.
Statistical methods used	Statistical methods used not specified
Results	SO_2: $y_i = a \cdot 1.45x_i^{-0.17}$; learning rate: 11%; progress ratio: 89% NO_x: $y_i = a \cdot 1.28x_i^{-0.18}$; learning rate: 12%; progress ratio: 88%

Assessment	SO_2: • The importance of R&D programs for process improvements may be significant. • Increased competition among vendors may have an impact on costs. • Uncertainties include the functional form (i.e., the assumption of a constant learning rate). NO_x: • There were significant improvements in catalyst manufacturing methods as well as increased competition, although there was no significant change in the price of precious metals.
Conclusions	Learning rates and progress rates are similar for both pollutants and are similar to other estimates for a wide range of market-based technologies.
Future research	• Explore the impact of different policy scenarios. • Longer time horizon
Other notes	N/A
Applicability to results	This study did not inform EPA's learning rate estimate because it is based on a limited number of data points (i.e., five data points each for FGD and SCR systems).
Themes	Learning rate estimations, Environmental technologies

Shinoda, Y., Tanaka, H., Akisawa, A., & Kashiwagi, T.

Article	**Evaluation of the plug-in hybrid electric vehicle considering learning curve on battery and power generation best mix**
Publication	*IEEJ Transactions on Power and Energy*, Vol. 129, No. 1, pp. 84–91
Date	2009
Industry examined	Plug-in hybrid electric vehicles (PHEVs)
Research question(s)	• Given different scenarios: How widely used will PHEVs be in the future? How much will the introduction of PHEVs reduce CO_2 emissions? Will there be serious effects on the power supply system? • Demonstrate an ideal scenario for PHEV introduction that minimizes the total cost in the passenger car sector and the power supply sector. • Estimate beneficial effects, including the reduction of CO_2 emissions.
Type of learning examined	Learning in general; Forecasting costs
Data sources	• Survey from METI Clean Diesel Passenger Car Study Council (2004) • *MLIT Road Traffic Census* (1999) • ANRE Power Development Outline (2006) • Comparative Cost of Power Generators by Model Calculation, ANRE Advisory Committee for Energy (2004) • Kaino, K. Power generation mix models and cost comparison. (2003) • Iwafune, Y. Comprehensive evaluation of CO_2 emission countermeasures in private sector, doctoral thesis (2000). • TENPES: Directory of Thermal and Nuclear Power Generation Facilities (2005) • Oda, T., Akisawa, A., & Kashiwagi, T. Method to estimate long-term change of heat and electric power daily load curves in Japan. IEEJ Trans PE (2005) • AIRIA: Number of Vehicles by Year of Registration, 1970–2006 • NPA Police White Paper: Number of Licensed Drivers by Age and Sex, 1970–2004 • Website of IPSS: Population Projection for Japan (2006) • METI: Recommendations for the Future of Next-Generation Vehicle Batteries (2006)
Data size	Unspecified
Data years	2010–2035 (based on projections)
Data adjustment	None
Methodology	The authors extend the linear model they previously developed (2008) which integrates power supply and passenger car models. The model is extended by allowing for renewals of car types and power sources as well as cost reductions due to the battery learning effect. The authors set up an objective function to be minimized, which is defined as the sum of the fixed and variable costs throughout the period. The objective function involves costs in the passenger car and power supply sectors. In the power supply sector, the authors consider the possible construction of new

	nuclear power plants, integrated coal gasification combined cycle plants, advanced LNG combined cycle plants, oil-fired thermal power plants, and pumped storage plants. Fixed costs include repair, labor, and initial construction costs. In the passenger car sector, the authors consider three car sizes (normal, small, and mini) and 11 categories differing by annual mileage. They consider four car types (gasoline vehicles, diesel vehicles, and gasoline hybrid electric vehicles (GHEVs), and PHEVs). The fixed cost is the initial cost divided by the age of service. For GHEVs and PHEVs, the battery cost is taken into account in the case of battery replacement. The authors incorporate the learning curve as follows. A certain battery cost is set as the initial value in each of the 5-year intervals and the integrated model is optimized. Then the battery cost is found from the cumulative battery quantity and the learning curve. The integrated model is optimized again using the new battery cost. This procedure is repeated until the difference in battery cost before and after optimization drops below some small value.
Statistical methods used	The authors use a multiyear extension of the linear integrated model of the power supply sector and passenger car sector and incorporating the learning effect of batteries by iterative calculations. The model minimizes the objective function, which is defined as the sum of fixed and variable costs throughout the period.
Results	The authors estimated the progress ratio to be 70% based on a regression analysis of actual data (using cumulative production and price).
Assessment	N/A
Conclusions	• For PHEVs to be accepted in 2030 as a standard passenger car type, the battery type in the first 5-year interval must be about 132,000¥ if batteries are not replaced, and about 125,000¥ if batteries are replaced. • If the official target of 100,000 ¥/kWh for the battery price in 2010 is achieved, the share of PHEVs among all new cars in Japan can exceed 60% in 2030 in the case of no-replacement. In this case, there is hardly any effect on the power supply construction schedule, but charging power requires an increase in power output of 2.3%. • Total CO_2 emissions in the passenger car and power supply sectors in 2030 can be reduced by about 100 Mt due to PHEV acceptance, even under limitations on the construction of nuclear power plants.
Future research	Extend the evaluation by considering other factors such as financial subsidies and CO_2 constraints.
Other notes	N/A
Applicability to results	This study did not inform EPA's learning rate estimate because it the authors used price as a dependent variable, which affected by market dynamics; hence, it is often out of the organization's control and is affected by many other variables.
Themes	Estimation of the progress ratio, Application of the learning curve

Appendix C. Summaries of Articles Related to the Mobile Source Sector that Received a Cursory Review

Contents

Alchian, A.

Article	**Reliability of progress curves in airframe production**
Publication	*Econometrica: Journal of the Econometric Society*, Vol. 31, No. 4, pp. 679–693
Date	1963
Industry examined	Airframe production
Research question(s)	• How long do labor costs decrease as the number of items produced increases? • Can learning be represented by a linear function on a double-log scale? • Does the reduction in labor costs fall at the same rate for different airframe manufacturing facilities? • How reliably can one predict marginal and total labor requirements for a particular production facility from an industry average progress curve derived from the experience of all airframe manufacturers? • How reliably can a curve fitted to the experience of all bomber (fighter) production predict labor requirements for a specific type of bomber (fighter) produced in a particular facility? • How reliable is a single manufacturing plant's own early experience for predicting its later requirements for producing a particular type of airframe? • What are the consequences of the margins of error involved in these estimating methods?
Type of learning examined	Learning by doing
Methodology; Quantitative or Qualitative?	Quantitative. The author estimated the average error of prediction that would occur if learning curves were fitted to the past performance of a facility in order to predict the facility's future requirements. The statistical methods included: (1) a visual examination of graphs, (2) analysis of variance tests, (3) tests whether the samples from each category (i.e., bombers, trainers, and fighters) are from populations with equal slopes, and (4) fitting specific progress curves to past performance of a facility.
Results	• Based on a visual examination of the graphs in the *Source Book of World War II Basic Data; Airframe Industry, Vol. I*, there is no evidence of any cessation in the decline in labor costs as the number of items produced increased, but the author stated he could not determine whether the decline would stop for a substantially larger number of items produced. • A linear function on a double-log scale is appropriate for a progress curve. • The progress curve slope or height is not the same for all model-facility combinations (MFCs). The relationships differ in slope and height even among the various facilities producing the same general type of airframe. Hence, individual MFCs do not have the same progress functions. • Using an industry-wide average progress curve, the absolute differences between predicted and actual values average 25% of the actual. • Using a general airframe-type progress curve, the weighted average of the errors was 25% (i.e., the ratio of the difference between predicted and actual values to the actual). Hence, there is no significant difference between the

	average learning coefficients by airframe type. • The average margin of error using a build-up progress curve is about 22%.
Conclusions	Before making decisions based on costs from predictions formed using historical data, researchers should investigate the range of uncertainty in the prediction.
Themes	Application of learning curves, Specification of the learning curve

Argote, L., Beckman, S. L., & Epple, D.

Article	**The persistence and transfer of learning in industrial settings**
Publication	*Management Science*, Vol. 36, No. 2, pp. 140–154.
Date	1990
Industry examined	U.S. wartime ship production
Research question(s)	• Does learning persist within organizations? • Does learning transfer across organizations?
Type of learning examined	Organizational learning by doing; Knowledge depreciation; Knowledge transfers across organizations
Methodology; Quantitative or Qualitative?	Quantitative. The authors used monthly data from the production of Liberty ships during WWII to estimate knowledge depreciation and knowledge transfers across shipyard by regressing production functions using maximum likelihood. The authors used tonnage as the outcome variable and cumulative output as one of the independent variables. The authors also used a calendar time separate the relationship between cost and technical progress associated with the passage of time from those associated with increasing cumulative output.
Results	• The monthly depreciation parameter ranges from .70 to .85, which implies that from a stock of knowledge available at the beginning of a year, only 1% to 14% of the stock would remain at the end of the year (=$.70^{12}$) and (=$.85^{12}$). • When a calendar time variable was introduced to the model, its negative coefficient indicates that the passage of time is not responsible for productivity improvements in shipbuilding. • There is no evidence of learning transfers. • Shipyards with later start dates were more productive than yards with early state dates. • Yards benefited from production at other yards up to their begin date.
Conclusions	• There was evidence that knowledge acquired from learning by doing depreciated: recent output was a more important predictor of current production than output from the more distant past. • There was evidence that learning transfers across organizations: organizations beginning production later were more productive than those with earlier start dates. That is, knowledge from the shipyards that began production early benefited those with later start dates. • Once organizations begin production, however, they did not appear to benefit from learning in other organizations.
Themes	Knowledge depreciation, Knowledge transfers across organizations

Bailey, M. N., Farrell, D., Greenberg, E., Henrich, J.-D., Jinjo, N., Jolles, M., & Remes, J. (McKinsey Global Institute)

Article	**Increasing global competition and labor productivity: Lessons from the US automotive industry**
Publication	Paper presented at the Federal Reserve Bank of San Francisco conference, "Productivity Growth: Causes and Consequences" (Nov. 18–19th, 2005)
Date	2005
Industry examined	US automotive manufacturing; specifically, production of new vehicles in the US, including parts assembly
Research question(s)	• How did the Big Three US original equipment manufacturers (OEMs) (i.e., GM, Ford, and Chrysler) respond to the changed competitive environment? • How did the Big Three overcome barriers to compete or fail to do so? • How did the Big Three's introduction of process and product innovations drive productivity growth? • How has regulation directly impacted on measured productivity and how has it influenced the competitive dynamics. • How does global competition change domestic sector dynamics and productivity growth? • How quickly do these changes occur and what factors determine the speed of adjustment? • What is the impact on stakeholders? • What can policy makers and companies elsewhere learn from the US auto sector experience?
Type of learning examined	Unspecified, but described learning in general. This study focuses on how increasing global competition leads to productivity growth
Methodology; Quantitative or Qualitative?	The authors used actual data to derive the relative contribution of OEMs and parts to productivity growth (Total productivity growth is the sum of the contributions). In a case study, the authors attributed the increases in productivity growth to specific actions taken by the OEMs.
Results	The authors found that nearly 45% of the productivity increase was driven by the Big Three's adoption of improved process technology; 25% came from the shift to new products with higher value-added per hour worked; and 30% came from increased features and quality in existing products, more efficient producers, and process efficiency improvements that have arisen from changes in product mix. The authors also found that each of the three phases in the evolution of a specific innovation had a different impact on productivity. The initial phase, which covers the initial development and introduction of the innovation, had a low impact on industry productivity. The second phase, adoption and learning, had a moderate impact on industry productivity. The third phase, penetration, when innovations become widely adopted within companies, and across the industry, drove significant changes in productivity.
Conclusions	Global competition forced the Big Three to raise labor productivity between 1987 and 2002 by introducing and adopting process and product innovations as well as

	by improving overall vehicle quality.
Themes	Decomposing sources of productivity growth, determinants of productivity growth, industry level, regulation's impact on productivity

Fisher, M. L., & Ittner, C. D.

Article	**The impact of product variety on automobile assembly operations: Empirical evidence and simulation analysis**
Publication	*Management Science*, Vol. 45, No. 6, pp. 771-786
Date	1999
Industry examined	Automobile assembly plants
Research question(s)	• Which dimensions of product variety affect measures of manufacturing performance such as labor productivity, rework, and inventory? • What is the magnitude of productivity losses due to product variety? • Which types of labor are most affected by product variety? • What are the specific mechanisms through which variety impacts productivity? • What is the ability of option bundling and the provision of direct labor slack in work stations with high product mix variability to minimize the adverse effects of increased product variety?
Type of learning examined	Although learning is not directly mentioned, this article relates to the debate described in Lapré & Nembhard (2010) regarding whether learning and performance are improved more through specialized or diversified experience.
Methodology; Quantitative or Qualitative?	Quantitative. Using three data sets (i.e., monthly data, daily data, and cross-sectional data for work stations) from a GM assembly plant, the authors use regression to examine the impact of product variety on plant performance. In addition, the authors perform a simulation analysis of a more general automotive assembly line to test the impact of option variability on direct labor productivity.
Results	• Empirical analyses: o Using monthly data: ▪ Greater option variety adversely impacts overhead productivity but not direct labor hours per car. ▪ Paid direct labor hours do not vary significantly with the number of options. ▪ Greater option variety increases overhead requirements. ▪ Increases in major rework account for the lower labor productivity in months with higher option variability. o Using daily data: ▪ The strongest determinant of direct labor hours per car is downtime in the body shop. ▪ Found no relation between paid direct labor hours and option content or option variability. o Using cross-sectional work station data: ▪ Workstations with more variability in option-related work content have more slack resources to compensate for this variation. • Simulation analysis: o The impact of option variety can be greatly reduced by buffering the assembly line and bundling options.
Conclusions	The authors found that option variability (i.e., the standard deviation in the number

	of the eight key options per car in a given month) has a significantly greater negative impact on productivity than option content (i.e., the average number of options per car). The authors also found that option variability increases overhead hours, rework, inventory, and the excess labor capacity assigned to a work station. But option variability does not significantly impact direct labor hours when labor slack is provided. The level of option variety has an insignificant impact on direct labor once the assembly line has been optimally buffered against process time variability with excess capacity. Bundling options can reduce the amount of buffer capacity required and random variation is more pernicious to productivity than product variety.
Themes	Automobile industry, Specialized vs. Diversified experience

Fisher, M., Ramdas, K., & Ulrich, K.

Article	**Component sharing in the management of product variety: A study of automotive breaking systems**
Publication	*Management Science*, Vol. 45, No. 3, pp. 297–315
Date	1999
Industry examined	Manufacturers of automotive breaking systems
Research question(s)	• What are the key drivers and trade-offs of component-sharing decisions? • How much variation exists in actual component-sharing practice? • How can this variation be explained?
Type of learning examined	The authors listed learning as one of the key drivers for component sharing because the quality and performance of a shared component may be higher than that of a component designed and produced for unique applications because learning is associated with increased volume.
Methodology; Quantitative or Qualitative?	Quantitative. The authors identified key costs related to component sharing and developed an optimization model to predict the ideal component sharing practice. Using the results from the optimization model, they formulated hypotheses about industrial practice and tested them using data from the automobile industry.
Results	• H1: Front brakes variety is increasing in $\sqrt{R_w V}$, a composite variable based on the range of weights and total remaining sales volume of all models in the product line of the manufacturer. o The number of brake rotors increases with the composite variable. • H2: Front brakes variety is a decreasing function of the variability in model volumes. o The number of brake rotors decreases as the variation in volume across different models increases. • H3: U.S. firms exhibit a greater amount of front brakes sharing than do the Japanese firms in the study. o Japanese companies share components less than the U.S. companies. • H4: Front brakes variety is an increasing function of product line variety. o There is a positive relationship between the number of products and the number of different brake rotors, which supports the hypothesis that the number of different components is driven by the number of different products.
Conclusions	• Component sharing is practiced in the industry according to an economic logic consistent with the authors' analytic model. • Their results are consistent with the theory that for a given total product volume, 'lumpiness" in the distribution of this volume gives rise to the possibility of opportunistically assigning unique rotors to the models with high volumes, while sharing components across the models with low volumes. • Japanese firms share less than U.S. firms for three possible reasons: (1) fixed costs of creating a new rotor may be lower for Japanese firms, (2) Japanese firms invoked heavyweight project organizations for product development more frequently than U.S. firms over the course of the study and therefore

	may lack cross-project coordination mechanisms, and (3) Japanese firms had higher design quality than U.S. firms, which is strengthened by the optimization of unique components. • The number of different components is driven by the number of different products. This may stem from (1) the tendency to design new products from scratch and (2) the tendency toward more autonomous project teams.
Themes	Learning as a cost driver for component sharing

Haunschild, p. R., & Rhee, M.

Article	**The role of volition in organizational learning: The case of automotive product recalls**
Publication	*Management Science*, Vol. 50, No. 11, pp. 1545–1560
Date	2004
Industry examined	Automakers
Research question(s)	• What is the role of volition in organizational learning? • Do firms learn better in response to internal procedures or external mandates?
Type of learning examined	Organizational learning
Methodology; Quantitative or Qualitative?	Quantitative. Using National Highway and Traffic Safety Administration data on auto makers' recalls, the authors use regression to examine the impact of cumulative production on subsequent recalls. In addition, they examine the impact of cumulative recall experience on subsequent recalls. Cumulative recall experience was separated into the number of voluntary and involuntary recalls. As an alternative, the author used the relative proportion of voluntary to involuntary recalls. Further, the authors test whether involuntary recalls cause shallow responses. The authors then add measures of generalism and specialism to the model to see if learning was affected differently due to this structural characteristic. The models included control variables (e.g., auto maker age, organization size, dummy variables to capture the effects of different presidential administrations, level of industry competition, and time trends).
Results	• Do auto makers learn from experience to reduce recalls? o Production experience reduces subsequent recalls. • Is subsequent recall performance affected more by voluntary or involuntary recalls? o Prior voluntary recalls reduce subsequent involuntary recalls, but there is no effect of prior involuntary recalls on subsequent involuntary recalls. o The higher the proportion of voluntary recalls, the lower the subsequent involuntary recalls. o Prior recalls (both voluntary and involuntary) increase subsequent voluntary recalls. o There is no effect of proportion of voluntary recalls on the subsequent voluntary recall rate. o Learning from involuntary recalls may be shallower and less likely to penetrate the organization or be stored in organizational memory. • Do generalists and specialists learn differently from involuntary and voluntary recalls? o Generalists do not have higher involuntary recall rates than specialists. o Generalists with a high proportion of voluntary recalls reduce their subsequent involuntary recall rates more than specialists. o Generalists learn more from voluntary recalls than specialists when the

	learning target is reducing subsequent involuntary recalls. o Generalists have more severe voluntary recalls than specialists. o Generalists and specialists do not learn differently from voluntary recalls.
Conclusions	Volition is an important determinant of the rate and effectiveness of learning because voluntary recalls result in more learning than mandated recalls. This is partly due to involuntary recalls resulting in shallower learning processes. The effect of volition differs for generalist and specialist auto makers.
Themes	Determinants of variation in learning rates, Automotive industry

Jaber, M. Y., Goyal, S. K., & Imran, M.

Article	**Economic production quantity model for items with imperfect quality subject to learning effects**
Publication	*International Journal of Production Economics*, Vol. 115, No. 1, pp. 143–150
Date	2008
Industry examined	Automotive industry
Research question(s)	How are the conclusions drawn from the economic order quantity (EOQ) model extended by Salameh and Jaber (2000) affected by learning?
Type of learning examined	Learning in general
Methodology; Quantitative or Qualitative?	Using data from an automotive manufacturer, the authors used an EOQ model from inventory literature, which allows managers to compute their order quantities, that was extended by Salameh and Jaber (2000) using the assumption that each lot size shipment contains a random fraction of imperfect quality items with a known probability distribution. The authors further extended this model by assuming the percentage of defective items in a shipment reduces in conformance with a learning curve (as was observed in practice). The authors created two mathematical models that optimize profit functions. The first assumes an infinite planning horizon, while the second assumes a finite one. The authors then applied parameters used by Salameh & Jaber in numerical examples.
Results	• The results of the model, which assumed an infinite planning horizon, suggest that the number of defective units, the shipment size, and cost reduces as learning increases. • The results of the model, which assumed a finite planning horizon, suggest that as learning becomes faster, one should order larger lots less frequently.
Conclusions	The authors found that the typical learning curve laid out by Wright (1936) cannot be viewed as the universal learning curve. The authors state that in practice, an S-shaped curve may be more appropriate. The S-shaped curve consists of three phases. The first phase features slow improvement as workers get acquainted. The most improvement occurs during the second phase. The third phase is the leveling of the curve. Wright's model would be good for situations with a short first phase.
Themes	Specification of the learning curve (power vs. exponential), Application of the learning curve, Automotive industry

Kim, I. & Seo, H. L.

Article	**Depreciation and transfer of knowledge: An empirical exploration of a shipbuilding process**
Publication	International Journal of Production Research, Vol. 47, No. 7, pp. 1857-1876
Date	2009
Industry examined	Shipbuilding
Research question(s)	The authors examined a learning curve model that overcomes the restrictions of period-based depreciation models and measures learning, transfers, and knowledge depreciation in one integrated framework that is governed by different rules (i.e., learning depends on cumulative units produced while knowledge depreciation depends on (1) the amount of knowledge accumulated and (2) the elapsed time between when knowledge is acquired and when it is used).
Type of learning examined	Learning by doing (direct learning); Learning from others (indirect learning or knowledge transfer), Knowledge depreciation at the organizational level
Methodology; Quantitative or Qualitative?	Qualitative and quantitative. The authors evaluate learning curve using log-linear, replacement, and accumulation models in the literature and proposed a new learning curve model that captures the acquisition of knowledge and its depreciation according to their distinction rules. They test their model using the WWII Liberty ship production dataset.
Results	• The learning rate for the most general model ranges from 0.3197 and 1.5822, which corresponds with a progress ratio that ranges from 33%–80%. • The monthly forgetting rate is approximately 26% in all three models, that is only 74% of knowledge available at the beginning of a month would remain by the end of the month. • Production cycle time could be reduced by 38.6%–46.5% through direct learning. • Production cycle time could be further reduced by 14.1%–18.7% through indirect learning.
Conclusions	The authors found that learning by doing is the major source of productivity growth. Indirect learning's potential contribution to productivity is about 40% of direct learning's contribution. They also found that knowledge depreciates rapidly (only 74% of knowledge available at the beginning of a month would remain by the end of the month). Hence, they conclude that knowledge depreciation and indirect learning should be included in learning curve model specifications aiming to estimate production rates and costs.
Themes	Estimated learning rates, Knowledge transfers; Knowledge depreciation, Learning curve specification

Levin, D. Z.

Article	**Organizational learning and the transfer of knowledge: An investigation of quality improvement**
Publication	*Organization Science*, Vol. 11, No. 6, pp. 630–647
Date	2000
Industry examined	Automotive industry
Research question(s)	• Does a learning curve for quality exist? If so, what form does it take? What factors influence it? • What happens during new product introduction, before the learning curve starts? Is there improvement in the "starting points" of learning curves? • Which type of learning, annual learning curve improvements or annual starting point improvements, has a greater impact?
Type of learning examined	Learning in general; Knowledge transfers
Methodology; Quantitative or Qualitative?	Quantitative. The author used panel data on automobile reliability factors (largely based on surveys) to estimate learning using ordinary least squares (OLS) regression with fixed effects. The author used repair rate as the outcome variable and cumulative output as one of the independent variables. The author then sequentially added the following independent variables: car model output; a time dummy; and sibling, cousin, division, firm, and Big Three output. In addition, the author tested for knowledge depreciation. Because the model's cumulative production output was insignificant, the author removed that variable and expanded the analysis using combinations of the following variables: fixed effects, a time dummy variable, a ceiling effect dummy variable, a year of production variable, interaction terms for the year of production with Ford and Chrysler dummy variables, a debut year variable, and control variables.
Results	H1: Learning curve • The estimated slope of the learning curve is -0.128 and -0.093 in the third and sixth year, respectively. A doubling of cumulative output led repair rates to fall by 8.5% ($2^{-0.128}$=0.915) and 6.2% ($2^{-0.093}$=0.938) in the third and sixth year, respectively. • On average, when a manufacturer has previously produced a lot of cars of a given model, that model's repair rate is lower. H2 and H2-ALT: Learning over Time • Once the author controlled for the average model's repair rate generally improving each year during its production life, the extent of a manufacturer's production experience for a particular model appeared to make no difference. • A year in a model's production life best predicts a model's ultimate repair rate. • There was no evidence of knowledge depreciation. • The estimated coefficients for the years of production seem to indicate a gradual reduction in repair rates for each subsequent year of a model's production life. • There is some evidence of a ceiling effect.

	H3: Transfer of Production-Based Knowledge • The data provide no evidence for the transfer of production-based knowledge on product quality, as measured by repair rates. • The study found no benefit to a model's repair rate from any measure of cumulative production experience, not for the model, its siblings, cousins, division, or firm. H4: "Debut-Year" Learning • The later a model begins its production life, the lower its baseline repair rate is. H5: Debut-Year Learning Versus the Learning Curve • An extra year of "debut-year" learning leads to better repair rates than does an extra year of incremental learning during a model's production life. A model's debut is an enhanced learning event.
Conclusions	• Stable learning curves are not limited to the cost or efficiency domain. They can include quality learning curves. • Some learning curves appear to be more a function of time than a function of cumulative experience. • Improvements to the starting point of some learning curves, when a product is first introduced, are even more important than improvements made during subsequent production. • The results suggest know-how brought in from outsiders does not accumulate as a function of their production experience, but the results also show that outside knowledge accumulates with the passage of time. Thus, manufacturers probably share quality-related knowledge across product families, divisions, and firms. Hence, there is knowledge transfer.
Themes	Learning in general, Knowledge transfers, Timing of learning, Determinants of variation in learning rates, Automotive industry

MacDuffie, J. P., Sethuraman, K. & Fisher, M. L.

Article	**Product variety and manufacturing performance: Evidence from the international automotive assembly plant study**
Publication	*Management Science*, Vol. 42, No. 3, pp. 350–369
Date	1996
Industry examined	Automotive assembly plant
Research question(s)	• What is the effect of increased product variety on manufacturing performance? • What are the consequence of different product strategies held by Japanese and US auto manufacturers? (Japanese manufacturers offer more distinct models, but fewer possible option combinations than U.S. manufacturers.) • What are the ways in which companies and plants attempt to minimize the impact of complexity on manufacturing performance?
Type of learning examined	The impact of plant characteristics and management practices on performance
Methodology; Quantitative or Qualitative?	Quantitative. The authors use multiple product complexity measures derived from the International Assembly Plant Study (i.e., model mix complexity, parts complexity, option content, and option variability), the production organization index (i.e., use of buffers, work systems, and human resource management policies), and control variables (i.e., automation, plant scale, and product design age) to test the impact of product variety on total labor productivity and quality using regression analysis.
Results	• The relationship between product complexity measures and productivity: o Model mix complexity had no statistical significant explanatory power with respect to productivity. o Parts complexity, option content, and option variability are statistically significant. o Parts complexity and option content had the expected positive signs, but the coefficient for option variability is negative, which was unexpected. • When the authors introduce each individual variable related to product complexity is introduced into the regression equation instead of the overall index: o The production organization index had a strong, statistically significant impact on productivity in that the more lean a plant was, the more productive it was. o The option content measure is no longer significant. o Lean production policies had little impact on parts complexity. • When examining the three component indices of the production organization index (i.e., the use of buffers, work system, and HR management policies) o The use of buffers index is not statistically significant. o The work systems and HR management policies are statistically significant.
Conclusions	Most of the product complexity measures did not have a negative impact on labor productivity or quality. Interestingly, option content had a negative relationship

	with productivity, while option variability had a positive relationship. However, parts complexity did have a persistent negative impact on productivity. The authors found support that management policies, in operations and human resource areas, can facilitate the absorption of higher levels of product variety. This implies that lean production plants (i.e., plants that use ongoing problem-solving processes on the shop floor and make incremental improvements) are capable of handling higher levels of product variety with less adverse effect on total labor productivity than traditional mass production plants (i.e., plants that use extra inventories or repair space to protect against potential disruptions).
Themes	Sources of variations in productivity, Automotive industry

Randall, T., & Ulrich, K.

<table>
<tr><td>Article</td><td>Product variety, supply chain structure, and firm performance: Analysis of the U.S. bicycle industry</td></tr>
<tr><td>Publication</td><td>Management Science, Vol. 47, No. 12, pp. 1588–1604.</td></tr>
<tr><td>Date</td><td>2001</td></tr>
<tr><td>Industry examined</td><td>U.S. bicycle industry</td></tr>
<tr><td>Research question(s)</td><td>How does product variety relate to supply chain structure?
How does matching product variety to supply chain structure affect firm performance?</td></tr>
<tr><td>Type of learning examined</td><td>The development of the authors' hypotheses are based, in part, on two assumptions related to learning: (1) economies of scale result, in part, through labor efficiency gains through learning and (2) that product variety exacerbates production costs when efficiency gains from learning are delayed as resources alternate focus among multiple products.</td></tr>
<tr><td>Methodology; Quantitative or Qualitative?</td><td>Quantitative. Using data from the U.S. bicycle industry (i.e., a buyer's guide and a survey on the supply chain structure), the authors tested their first hypothesis using ANOVA to compare the mean level of variety across different structural options and they tested their second hypothesis using ordinary least-squares (OLS) regression.</td></tr>
<tr><td>Results</td><td>Hypothesis 1 tested whether firms using scale-efficient production processes will have higher levels of production-dominant variety that firms using scale-inefficient process and whether firms with plants located within target markets will have higher levels of market mediation-dominant variety than firms located away from the target market.
Production-dominant variety is positively associated with scale-efficient/distant production
Market-mediation dominant variety is positively associated with scale-inefficient/local production
Hypothesis 2 tested whether firms matching production-dominant variety with scale-efficient production and mediation-dominant variety with local production outperform firms which fail to make such matches.
Firm performance is positively associated with correctly matching supply chain strategies to product variety strategy.</td></tr>
<tr><td>Conclusions</td><td>Firms which match their supply chain structure to the type of product variety they offer outperform firms which fail to match such choices.</td></tr>
<tr><td>Themes</td><td>Application of learning, Determinants of variation in learning rates</td></tr>
</table>

Rapping, L.

Article	**Learning and World War II Production Functions**
Publication	*The Review of Economics and Statistics*, Vol. 47, No. 1, pp. 81–86
Date	1965
Industry examined	U.S. wartime shipbuilding
Research question(s)	What is the role of organizational learning resulting from accumulated production experience?
Type of learning examined	Learning at the organizational level. (Individual learning is not measured.)
Methodology; Quantitative or Qualitative?	Quantitative. Using data from 15 shipyards, the author estimated the parameters of a production function with standard least squares using the log of annual rate of physical output as the dependent variable and the log of the annual rate of physical labor and capital inputs as independent variables. The author tests variations of the model by adding time variables (i.e., calendar and yard time), cumulated output variables (i.e., using three varying definitions), and a variable for annual rate of output of ship types other than Liberties.
Results	The author found increasing returns to proportionate changes in labor and capital inputs. Neither a time variable nor a cumulated output variable could explain away this finding. Evidence also showed that cumulated output could account for productivity increases, which the author attributed to learning or adaption. The author noted the effect of cumulated output on productivity is sensitive to the definition of cumulated output. When using calendar time and yard time as the independent variable, each doubling of time is accompanied by a 23% and 28% increase in the rate of output, respectively. When using only cumulated output as the independent variable, each doubling of time is accompanied by an 11%–29% increase in the rate of output depending on which measure of cumulated output was used. When controlling for time, the author found each doubling of cumulated output is accompanied by a 12%–34% increase in the rate of output (depending on which measure of cumulative output was used). Thus, estimated progress ratios ranged from 66% to 88%. The results suggested the cumulated output had a relationship with productivity independent of other variables correlated with time.
Conclusions	The author finds evidence of learning while controlling for time, using various definitions of cumulated output, and controlling for economies of scale. The paper advanced the state-of-the -art at the time by controlling for economies of scale. Evidence of learning was found when economies of scale were controlled.
Themes	Estimated learning rate

Thompson, P.

Article	**How much did the Liberty shipbuilders learn? New evidence for an old case study**
Publication	*Journal of Political Economy*, Vol. 109, No. 1, pp. 103–137
Date	2001
Industry examined	U.S. wartime ship production
Research question(s)	Do previous learning by doing studies on Liberty ships suffer from omitted variable bias (specifically capital investment and quality changes)?
Type of learning examined	Learning by doing
Methodology; Quantitative or Qualitative?	Quantitative. Equipped with new data on capital investment from the National Archives, Thompson expanded on the work done by Rapping (1965) and Argote, Beckman, & Epple (1990). Using seemingly unrelated regression estimation, the author estimated a temporal production function which incorporated a measure of all physical capital structures and non-structures whereas the production functions used by Rapping and Argote et al. only used a subset of structures. The outcome variable was monthly deliveries per yard and the independent variables used for experience were either cumulative output or cumulative labor hours. Thompson estimated the learning rate while controlling for capital investments and quality and compared his results with those from Rapping and Argote et al.
Results	• Using cumulative output as the independent variable, the authors estimated the following learning coefficients: o Rapping: 0.110, which corresponds to a progress ratio of 93% o Argote et al.: 0.44, which corresponds to a progress ratio of 74% o Thompson: 0.263–0.493, which correspond to a progress ratio of 71%–83% • Using cumulative employment as the independent variable, Thompson estimates a learning coefficient of 0.208–0.359, which corresponds to a progress ratio of 77%–87%.
Conclusions	Two omissions from previous research led to overestimation of learning rates: investment in physical capital and variations in product quality. Capital deepening was more extensive than assumed and part of the increase in productivity came at the expense of quality, which accounted for 50% and 5% of the increase in labor productivity, respectively.
Themes	Specification of the learning curve, Estimated learning rate

Thompson, P.

Article	**How much did the Liberty shipbuilders forget?**
Publication	*Management Science*, Vol. 53, No. 6, pp. 908–918
Date	2007
Industry examined	U.S. wartime ship production
Research question(s)	• What is the rate of organizational forgetting of U.S. wartime ship production? • Do unobserved changes in a firm's product mix produce spurious evidence for organizational forgetting? • Is the estimated rate of organizational forgetting sensitive to assumptions made about the learning process? • Does labor turnover influence productivity?
Type of learning examined	Organizational forgetting
Methodology; Quantitative or Qualitative?	Quantitative. Using data from the National Archives, the author expanded on the quantitative analysis done by Argote, Beckman, & Epple (1990) using regression analysis to estimate the depreciation parameter using a (1) a loglinear learning-forgetting model, (2) accumulation model, and (3) a replacement model. The author also tested whether labor turnover is correlated with productivity by adding the recorded rates of labor hiring and separation as a level effect.
Results	• The monthly depreciation rate ranged from 5.8% to 8.4%. When correcting for the product mix, the monthly depreciation rate ranged from 3.6% to 4.2%. This implies that 49% to 64% of the knowledge stock at the beginning year would remain at the end of the year. (=$(1-0.058)^{12}$) to (=$(1-0.084)^{12}$) • When testing for the effect of labor turnover, the author found that increased labor turnover either has no effect on productivity or raises it.
Conclusions	The estimated rate of organizational forgetting was less than in previous studies analyzing the same data. Argote et al. (1990) estimated a 25% monthly rate of knowledge depreciation. The author's estimates ranged from 3.6% to 5.7%. The author found that controlling adequately for changes in a firm's product mix has significant effects on the estimated rate of organizational forgetting, but the estimated rate of forgetting was only moderately sensitive to the specification of the learning curve. In addition, the author found that labor turnover was largely unrelated to productivity changes. When labor turnover was included in the model, organizational forgetting did not appear to occur.
Themes	Knowledge depreciation, Estimated organizational learning rate, Specification of the learning curve

Thornton, R. A., & Thompson, P.

Article	**Learning from experience and learning from others: An exploration of learning and spillovers in wartime shipbuilding**
Publication	*American Economic Review*, Vol. 91, No. 5, pp. 1350–1368
Date	2001
Industry examined	U.S. wartime shipbuilding
Research question(s)	What is the importance of leaning spillovers? Specifically, are learning spillovers sufficiently large for on-the-job learning to be a plausible source of long-run growth? Are external spillovers larger enough for the suboptimality of production to be a cause for concern?
Type of learning examined	Learning spillovers
Methodology; Quantitative or Qualitative?	Quantitative. Using an expanded dataset (including non-Liberty ships and shipyards), the authors estimated spillovers by fitting a parametric and a semi-parametric production function using ordinary least-squares (OLS) estimation. The dependent variable is the realized labor requirement. The independent variables include capital stock, total labor hours, calendar date on which the keel was laid, a vector of experience consisting of four elements to capture learning and spillover effects.
Results	• Cross-yard spillovers within the same product design were almost as important as own-yard learning effects. The potential effect of cross-yard spillovers within the same product design is estimated to have been about 88% of the potential effect of own-yard experience. • The reduction in the unit labor requirements obtained from an extra unit of experience in the same product design is 5 times as great as the increase obtained from an extra unit of experience on prior designs. • The maximum contribution of learning spillovers across yards is found to be 106% of the combined contribution of the two types of within=yard learning.
Conclusions	The authors found that learning spillovers, across products and across yards, were a significant source of productivity growth. The spillover effects may have been more important than conventional learning effects. In addition, the size of learning externalities across yards was small. Together these findings suggest that spillovers help firms grow, but market failures induced by learning externalities are modest. In terms of the conventional learning effect, the authors found that the learning effect is positively sloped and concave. It exhibits rapid rates of learning at early stages and strong negative effects at higher levels of experience.
Themes	Learning spillovers, Learning externalities

Tsuchiya, H. & Kobayashi, O.

<table>
<tr><td>Article</td><td>Mass production cost of PEM fuel cell by learning curve</td></tr>
<tr><td>Publication</td><td>International Journal of Hydrogen Energy, Vol. 29, No. 10, pp. 985–990</td></tr>
<tr><td>Date</td><td>2004</td></tr>
<tr><td>Industry examined</td><td>Proton exchange membrane (PEM) fuel cells for automobiles</td></tr>
<tr><td>Research question(s)</td><td>Is it possible to reduce the cost of PEM fuel cells through learning?</td></tr>
<tr><td>Type of learning examined</td><td>Learning in general</td></tr>
<tr><td>Methodology; Quantitative or Qualitative?</td><td>Quantitative (simulation using assigned progress ratios). The authors use a learning curve to estimate the future cost reduction in fuel cell stacks due to mass production. Using predicted values, the authors constructed nine scenarios with combinations of power density improvement (three scenarios) and cost reduction speed (three scenarios). For each of the three cost reduction speed scenarios, the authors assigned a different progress ratio. Using the nine scenarios, the authors estimated the resulting cost of the overall fuel cell stack and its components.</td></tr>
<tr><td>Results</td><td>The following table presents nine scenarios of fuel cell stack costs based on combinations of power density improvement and cost reduction speed. The progress ratios for power density improvement and cost reduction speed are in parentheses.
<table>
<tr><th>Scenario (Progress Ratio)</th><th>High Power Density (94.5%)</th><th>Medium Power Density (96%)</th><th>Low Power Density (97.5%)</th></tr>
<tr><td>Rapid (78%)</td><td>$88/kW</td><td>$103/kW</td><td>$121/kW</td></tr>
<tr><td>Moderate (82%)</td><td>$143/kW</td><td>$167/kW</td><td>$196/kW</td></tr>
<tr><td>Slow (88%)</td><td>$285/kW</td><td>$334/kW</td><td>$392/kW</td></tr>
</table></td></tr>
<tr><td>Conclusions</td><td>The authors estimated that by 2020, it would be possible to reduce a fuel cell stack cost enough to be comparable to the cost of the internal combustion engine (which is used today) if it was mass produced. In addition, the authors found an improvement in power density would be essential to decreasing the overall stack cost because it would decrease the resource use of other materials per unit power output.</td></tr>
<tr><td>Themes</td><td>Application of the learning curve</td></tr>
</table>

Appendix D. Responses to Peer Review Comments

This report has undergone peer review according to the guidelines set forth in EPA's Peer Review Handbook (U.S. EPA, 2015). The peer review was independently managed by RTI International (RTI). RTI selected the following three peer reviewers: Dr. Natarajan Balasubramanian of Syracuse University; Dr. Marvin Lieberman of the University of California, Los Angeles; and Dr. Chad Syverson of the University of Chicago.

Appendix D contains the summaries of the peer review comments and responses to each comment. Most comments were addressed directly in the report. For these comments, we will indicate the section where the updates can be found. If no changes were made to the report based on the peer review feedback, we explain our reasoning for not doing so. EPA retained the original contractor, ICF, and the SME, Dr. Argote, who developed this report to prepare responses to certain comments.

We categorized summaries of the comments into the following 11 groups organized by topic area: (1) the report in general, (2) background and summary, (3) the recommended progress ratio, (4) the literature review in general, (5) the literature review on sources of learning variation, (6) the literature review on knowledge persistence and depreciation, (7) the literature review on knowledge transfer and spillovers, (8) the literature review on the location of knowledge, (9) the literature review on the specification and aggregation of learning, (10) the literature review on the application of the learning curve, and (11) typographical errors and other minor corrections.

General Comments

#	Peer Reviewer	Peer Reviewer Comment	Response
1	Lieberman	The report is comprehensive, and does a good job of characterizing the rates of learning typically found in transportation equipment manufacturing plants. Compared with Argote's (2013) book or any individual research study, this report offers a more in-depth view of the literature on industrial learning that is most relevant to the mobile source sector. Overall, the report is a well-executed document that is likely to be helpful in providing a basis for incorporating forecasts of learning into EPA and other government rulemakings. Despite these strengths, the report has a number of limitations that should be acknowledged more clearly. There are several areas where improvements can be made in the document.	See the "Summary and Background" section.
2	Syverson	On balance, the study is a very fine review of the literature on learning by doing in general,	See the "Summary and Background" section.

#	Peer Reviewer	Peer Reviewer Comment	Response
		especially with regard to its manifestation in manufacturing operations during the past few decades. The report is notably comprehensive within this scope, makes sensible topical categorizations in its discussion of the literature's findings, and is clearly written. The report achieves the intended goal of being a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically.	
3	Balasubramanian	The overall presentation and organization of the report is generally clear. However, there are some specific areas that require greater clarity.	See the "Summary and Background" section.

Background and Summary

#	Peer Reviewer	Peer Reviewer Comment	Response
4	Balasubramanian	The report appears to have multiple objectives that are stated in several places. In addition, there is at least one aspect that is provided in the report but not mentioned as an objective (i.e., the methods of forecasting in Appendix A). I recommend a short subsection that explicitly states the objective(s) in one location. In addition, I recommend that the document refer to these objectives consistently throughout the document. For instance, Objectives 3 and 4 above are similar but it is not clear what the difference between a "reliable" and a "best" estimate is. It may be more appropriate to choose one of them, and use that consistently. Also, note that the term "best estimate" has a generally accepted econometric definition as the estimate with the lowest variance among a set of estimates. Hence, it may be prudent to avoid using that term or to clarify its meaning as used in this report.	See updated discussion about the report's objectives in Section 1, "Introduction." We refer back to these objectives throughout the report. In addition, we replaced the term "best" or "reliable" estimate with "summary effect" following the example of Borenstein et al. (2009).
5	Balasubramanian	The two paragraphs in Section 3.2 beginning "Learning is a major source of…." do not directly relate to the discussion in Section 3.2, "What are Progress Ratios?" and appear out of place. I recommend that they be moved to the Section 3.3, "Summary of Literature Review."	This discussion has been moved to Section 3, "Summary of Literature Review."

#	Peer Reviewer	Peer Reviewer Comment	Response
6	Balasubramanian	The report does not seem to provide a clear summary of the literature review. The summary in the "Summary and Background" section of the report focuses almost entirely on the estimation of the average progress ratio, which is only a small part of the review. The summary in Section 3.3 is only a table with no additional explanation. I recommend that a more descriptive summary of the literature review be included. Among others, I suggest that the summary highlight the variation observed in the rates of learning-by-doing (currently discussed in Section 4).	See the "Summary and Background" section and Section 3.3, "Summary of Literature Review."
7	Balasubramanian	Section 1 of the report (paragraph 4) states, "It will also summarize empirical estimates of the learning effect separately for each of the specific mobile source industries (e.g., original equipment auto makers, parts suppliers to those auto makers, loose engine manufacturers, large truck manufacturers, and nonroad equipment manufacturers) for which studies are found that address those specific sectors." This break-down by industry is not provided in the report. The report provides only one estimate for the entire sector. Hence, this statement should be corrected or placed in a different context (e.g., the original intent of the study was to summarize empirical estimates separately…).	See Section 1, "Introduction."
8	Balasubramanian	Section 2 of the report provides two reasons for not providing a break-down of progress ratios by industry. The <u>first</u> is the lack of studies in many of the individual industries and the <u>second</u> is the greater within-industry variation in rates of learning-by-doing as compared to inter-industry variation in those rates. While the first has merit, the second is not a valid reason for not providing a break-down by industry. It raises the question of why studies from outside the mobile source sector should not be used for estimating the "best" or "reliable" progress ratio for the mobile source sector. In my opinion, since there is significant variation across industries (albeit less than the within-industry variation) in the average progress ratios (e.g., see provided progress ratios or Dutton & Thomas, 1984), it is appropriate to consider using industry-specific estimates, if and when such estimates become available. In general, it will be more informative to use the means of two sub-groups than the mean of the group as a whole.	See Section 2, "Selection of Subject Matter Expert and Identification of Relevant Learning-Related Studies."

Recommended Progress Ratio

#	Peer Reviewer	Peer Reviewer Comment	Response
9	Lieberman	I agree that the weighted average progress ratio across the five selected studies is 84.3%. Moreover, based on my experience and my reading of the broader literature on learning curves, this is not an unreasonable figure for manufacturing cost projections and forecasting in the mobile source sector (at least for plants of the type surveyed by the five studies). However, the claim that there is a 95% confidence interval of 83.9% to 84.8% is misleading. That statement of the confidence interval overstates the precision of the estimate. [The method used would be appropriate if there were some underlying, universal rate of learning in the mobile source sector. That is unlikely; the data show there is variation in the rate of learning.] Rather than taking the (weighted) average value of 84.3% across the five studies, if one chose to be more conservative, a reasonable choice would be to use the smallest rate of learning in the sample, that is, the progress ratio of 87%. In any case, the estimates from these five studies all lie in a fairly close range. Depending on the purpose at hand, one could justify using 84.3%, or 87%.	See Section 3.4, "Discussion of Mobile Source Results and Recommendations."

#	Peer Reviewer	Peer Reviewer Comment	Response
10	Lieberman	All five of the plants that are studied in this sample are engaged in final assembly of transportation equipment (trucks, automobiles and airplanes). Thus, the progress ratio estimates are indicative of plants of this type, that is, assembly plants for relatively complex mechanical products made on a production line. The estimates may not be suitable for plants producing other types of products or plants using other types of processes. For example, the article by Nykvist and Nilsson (2015) that surveyed dozens of studies on learning in the production of Li-ion battery packs, found a learning rate of only 9% for the overall industry and 6% for the leading manufacturers. This is a much lower learning rate than the 84.3% progress ratio observed on average across the five selected studies.	See discussion in Section 3. 4, “Discussion of Mobile Source Results and Recommendations.” For a response to the comment about Nykvist and Nilsson (2015), please see Comment #36 under “Literature Review – Application of the Learning Curve (Previously Section 4.6)” below.
11	Lieberman	A further deficiency in the report is the failure to point out that the progress ratio estimates in the five selected studies are not based upon the total cost of production. All five studies in the final sample focus on assembly plants for transportation equipment. None of the studies utilizes data on the total costs per unit of output in these plants. Rather, four of the studies focus on labor costs and labor productivity in the assembly plant (vehicles produced per labor hour, or labor hours per aircraft), and one study focuses on defect rates. An 84.3% progress ratio based on labor cost reflects a 15.7% savings in labor cost per unit for each doubling of cumulative output. It does not imply a 15.7% savings in total cost per unit for each doubling. Thus, any forecast of reduction in total unit cost depends on (1) the progress ratio multiplied by the growth in cumulative output (number of “doublings”) in the assembly plant, as well as (2) the progress ratio and change in cumulative volume applicable to the production of the component parts. The report should be clear about this need to consider cost reduction of the component parts as well as the learning curve in the final assembly plant. If a new vehicle model is produced with new component parts, the rates of cost reduction for parts production and final assembly are likely to largely coincide (so	See discussion in Section 5, “Responses to Peer Reviewer Comments Related to the Analysis.”

#	Peer Reviewer	Peer Reviewer Comment	Response
		that a single progress ratio can be used), but this need not be the case. Similarly, the report is unclear and misleading in describing the nature of the cost analysis in the five representative studies. The "unit costs" analyzed in the five studies are essentially labor costs, or unit costs of final assembly, per se. The studies do not tell us the extent to which the total cost per unit, including the cost of the component parts, followed a similar progress ratio.	
12	Syverson	I have a couple of comments about the standard error of the "meta-estimate" calculated in the report. First, it would be helpful if the report offered a brief explanation of how this standard error is calculated from the literature's values cited in Table 2. While the point estimate of -0.245 is described as an inverse-variance-weighted average of the five point estimates, the standard error is left unexplained. If the calculation is complex, it need not be spelled out line-for-line; a short description of the calculation's intuition would be enough. Second, and more substantively, is the possibility that the standard errors across the five studies in Table 2 vary for reasons besides just sample size differences. There are, after all, some basic differences across the studies (e.g., industry and outcome measure). In some ways—and the report notes this—the fact that despite these differences their estimates are all markedly similar might suggest inferring that any heterogeneity across the studies is more or less orthogonal to the learning rate. On the other hand, it is not practically possible to statistically reject heterogeneous parameters with respect to covariates such as industry and outcome measures, with only five observations. As with the gross-versus-net distinction discussed above, I do not know if there is any straightforward way to quantitatively address this issue, but it strikes me as something worth discussing a bit more in the report.	See Section 3.4, "Discussion of Mobile Source Results and Recommendations."
13	Balasubramanian	The overall conclusion that learning-by-doing occurs in the mobile source sector is well-founded and largely indisputable.	We added this comment in a footnote in Section 1, "Introduction."

#	Peer Reviewer	Peer Reviewer Comment	Response
14	Balasubramanian	The methodology for estimating the weighted-average progress ratio from the five studies is broadly reasonable. In particular, the following executive decisions related to estimating the average progress ratio appear reasonable given the objectives of the report: a. Focusing only on studies that examine unit costs and excluding studies that use other measures of performance b. Excluding studies of learning-by-doing in shipbuilding during the Second World War due to the uniqueness of the context	We added this comment to a footnote in Section 3.4, "Discussion of Mobile Source Results and Recommendations."
15	Balasubramanian	The report uses a "fixed-effects" model to combine estimates from different studies (the weight is the inverse of the variance). However, it is not clear that all studies used the same method to computing standard errors. For instance, some studies may have computed heteroscedasticity-robust or clustered standard errors, which would typically be larger than studies that assume homoscedasticity. If that is indeed the case, taking a simple inverse would not be accurate, and presenting one or more alternative estimates in addition to this "fixed effects" estimate (e.g., a simple average) may provide a more complete picture. An additional rule can be applied if one of these estimates has to be chosen (e.g., the most conservative). The methodology for estimating the standard error of the average progress ratio is not explicit in the report. A sentence or two describing this should be added in Section 3.4. Though the estimate of the weighted-average progress ratio is broadly reasonable, the discussion about the uncertainty associated with learning-by-doing is quite sparse. Such a discussion is important for a full understanding of the weighted-average progress ratio. <u>The standard error of the weighted-average progress ratio is likely to be small</u>, as currently stated in the Report. However, that small standard error does not reflect the true variation in the progress ratios across organizations and contexts, which is likely to be significantly larger. Also, some important aspects of the studies need highlighting to provide readers a better understanding of their context (which could be possibly different from today's context or other	See discussions in Section 3.4, "Discussion of Mobile Source Results and Recommendations." We reviewed Benkard (2000) and Levitt et al. (2013) to see how they calculated standard errors. Both authors controlled for heteroscedasticity, but only Benkard controlled for autocorrelation and serial correlation.

#	Peer Reviewer	Peer Reviewer Comment	Response
		contexts in the mobile source sector). Hence, providing a prominent contextual discussion in the "Summary and Background" section of the report and in Section 3.4 covering the following aspects is recommended: a. There is significant variation and uncertainty in the rates of learning-by-doing depending on many factors, and that learning-by-doing is not automatic as discussed in Section 4. b. The specific empirical context of the five studies, viz. the production of a new car model, as well as the dates of these studies (where available). These aspects are currently discussed in different places in the report but it is important that a summarized version of these points be located close to discussions of the weighted-average progress ratio.	
16	Balasubramanian	The report aims to get a "best" or "reliable" estimate of the "effect" of learning-by-doing (or cumulative output) on costs. The term "effect" has a causal connotation. However, it is not clear that all five studies used econometric techniques to causally estimate the effect of learning-by-doing. If so, it may be more appropriate to characterize the estimated weighted-average progress ratio as the association between unit costs and cumulative output, rather than as the effect of learning on costs. This approach is also consistent with the decision to focus on models that include only cumulative output as a predictor instead of using a more complete model that includes other factors. This decision implies that the effect of other factors is not isolated from the effect of cumulative output, when estimating the weighted-average progress ratio.	We maintained our use of the term "learning effect." We added a discussion to the introduction explaining how we define "learning effect" and how it is used in the report. We also added a discussion about how difficult it is to prove causation and how it can be done with controlled laboratory experiments. See Section 1, "Introduction." We did, however, replace any terms that infer causation from our summaries of the 18 articles in the report.

#	Peer Reviewer	Peer Reviewer Comment	Response
17	Balasubramanian	As discussed in the report, cumulative output can be correlated with many other factors (e.g., economies of scale). Also, the estimated weighted-average progress ratio in the report uses models that include only cumulative output as a predictor. Hence, forecasting the impact of learning-by-doing alone based on that ratio is not possible in the absence of information on the other factors. However, this does not render the forecasting exercise provided in Appendix A meaningless. It still measures the likely change in unit costs due to a change in cumulative output, which could be due to learning-by-doing or due to other factors. Recognizing this assumption implicit in these methods is important, especially when applying these methods.	We elaborate our discussion in Section 3.4, "Discussion of Mobile Source Results and Recommendations."

Literature Review – General

#	Peer Reviewer	Peer Reviewer Comment	Response
18	Lieberman	Given that the final recommendations in the report are based almost exclusively upon the five selected studies, it is useful for a reader to be able to review a detailed summary of these studies. Four of the studies are summarized in Appendix B. However, the (truck plant) study by Argote, Epple, Rao, and Murphy (1997) does not seem to be included in Appendix B. I recommend that a summary of this study be added to the appendix. Moreover, it might be helpful to add some additional information to Table 2, which very briefly summarizes the five selected studies. This information might include the dependent variable. While this can be determined from Table 1, it is awkward for a reader to have to search and scan between these sections. Table 2 might also indicate the pages in the appendix where the summary of each study can be found.	We did not review the working paper from Argote, Epple, Rao, & Murphy (1997) because it was not able to be published due the proprietary nature of the data. The progress ratio used in Table 2 was taken from Argote's (2013) description of the Argote et al. (1997) study. We clarified the citations to show this. In addition, we added a column to Table 2 that indicates the outcome variable used by the author(s). We referred readers to the detailed summaries in Appendix B under the list of authors and publication date in Column 1.

#	Peer Reviewer	Peer Reviewer Comment	Response
19	Lieberman	In general, I find the literature review to be comprehensive and informative. One specification issue that is left hanging in the report is whether the learning curve should be estimated with an initially "steep" portion followed by a "flat" portion (once the data have been transformed into logarithms). This specification issue is raised on the last page of the "Summary and Background" section; however, there is no specific follow-up in the report. (Virtually all of the presentation in the report is consistent with a single learning curve that does not change slope over time.) This issue of whether the slope of the learning curve is constant or diminishing should be discussed, and ideally, resolved in the report.	See discussion in Section 5, "Responses to Peer Reviewer Comments Related to the Analysis."
20	Syverson	The only recent paper on learning by doing in manufacturing that I did not see discussed in this study is Hendel and Spiegel (American Economic Journal: Applied Economics, Jan. 2014). That said, the paper's setting is not in mobile source manufacturing, and it is a judgment call whether the paper warrants any more attention than a cursory review for the purposes of this study.	We gave this article about learning in general a cursory review. This article did not receive a general review for two main reasons. For one, the study was not related to the mobile source sector. Secondly, the authors include a time trend variable in every model that included a cumulative output variable. Including both variables in the same models could have introduced multicollinearity into the results. This could potentially explain why both variables were insignificant.
21	Syverson	There are several points in the report where contrasts are made between measures of the outcome variable in learning by doing estimation. The report rightly points out (e.g., page 13) that using price or any metric that embodies price is likely to confound supply-side learning effects with demand-side changes that could be unrelated to the learning process. For example, this concern applies to value added. However, it applies equally to shipments as an outcome variable. The report holds out shipments as problematic because they include any inventory accumulation or de-accumulation, and that is true, but shipments are also reported in real dollar values, raising the supply-versus-demand conundrum. This fact was not always made clear in the text. For example, when shipments are mentioned on page 13, only the inventory issue is raised, and	See Section 3.3, "Summary of Literature Review."

#	Peer Reviewer	Peer Reviewer Comment	Response
		moreover the output measure of Bahk and Gort (1993) is described as "the number of shipments." Perhaps I am just interpreting the wording differently than the sense in which it was meant, but this sounds like a quantity of units of a good rather than a dollar value.	
22	Syverson	I completely agree with the study's interpretation of the literature that heterogeneity in learning rates could well be large across organizations, even within an industry, than across industries. This is a very useful point to make.	We added this comment to a footnote in Section 4, "Review of Learning Curve Literature by Topic."
23	Balasubramanian	The overall approach to the review—identifying studies of learning-by-doing in the mobile source sector, reviewing them for relevance to the goals of the study and identifying a shorter list of relevant studies for more detailed review—appears reasonable. The list of topics included in the review and the coverage of those topics appear broadly reasonable.	We added this comment to a footnote in Section 2, "Selection of Subject Matter Expert and Identification of Relevant Learning-Related Studies."
24	Balasubramanian	The set of articles related to progress ratio estimation in the mobile source sector and included for review appears to be reasonably comprehensive. A search for articles on learning-by-doing in the mobile source sector on Google Scholar did not yield any new substantively-contributory articles on this subject. A possible, but not necessary, addition is Balasubramanian and Lieberman (2011). The article itself is not relevant, but the Online Appendix to this article contains estimates of new-plant learning-by-doing using different methods for several industries, at a more fine-grained level (at the SIC-4 level) than Balasubramanian and Lieberman (2010).	We would like to thank the commenter for the additional data from his 2010 article. Because the dependent variable used in the study (i.e., real value added) was not appropriate for the goals of this study (See discussion in Section 3.3) and the range of progress ratios provided was large, the additional data will not be used to inform our estimate. After conducting a cursory review of the 2011 article, we agreed that it was not relevant to the goals of this study.
25	Balasubramanian	Based on a broader search of articles on learning-by-doing, an article (Haunschild and Rhee, 2004) may potentially add some insights in Section 4.1, but not including it will not detract substantively from the findings of the Report.	We gave this article a cursory review and added a summary to Appendix C, "Summaries of Articles Related to the Mobile Source Sector that Received a Cursory Review."

Literature Review – Sources of Learning Variation (Section 4.1)

#	Peer Reviewer	Peer Reviewer Comment	Response
26	Lieberman	The report provides no guidance on how to perform a cost analysis forecast that incorporates learning and economies of scale as separate elements. Perhaps the text should be more explicit about this, although the last paragraph of Section 3.3 ("Column 6 – type of outcome variable") makes it clear that the report is focused on using only cumulative output as a predictor. When controls for economies of scale are omitted from the analysis, the estimated progress ratio includes the effects of both learning and scale economies. This has been shown in a number of studies (e.g., my 1984 article on chemical products). Adding a separate parameter for economies of scale normally improves the statistical fit, but the improvement is seldom dramatic, and most studies have found scale economies to be less important than the learning effect. Moreover, if the data sample is small, colinearity between the learning and scale parameters can reduce the accuracy with which each is estimated. <u>One implication is that if the analyst or policy maker is able to apply only a single cost driver for forecasting purposes, application of a learning curve or progress ratio to forecasted cumulative output may provide the best projection of future costs</u>.	See discussion in Section 5, "Responses to Peer Reviewer Comments Related to the Analysis."
27	Lieberman	I am puzzled that the findings from the Balasubramanian and Lieberman (2010) article are heavily discounted because the learning rate "was estimated using revenues less materials costs (i.e., value added) as the outcome variable, rather than unit cost." None of the five studies selected as representative of the mobile source sector actually utilize data on unit cost. Four of the studies use data that correspond to value added in final assembly, omitting materials costs. Thus, the dependent variable in the article from Balasubramanian and Lieberman is not so different from those of the selected studies. (However, Balasubramanian and Lieberman estimate a learning rate over the life of the manufacturing plant, rather than over the life of a new product within the plant.) I provided data to show that the average learning rates by 4-digit SIC code for the mobile source sector are substantially in line with those in the summary section of the report.	Lieberman's 2010 study with Balasubramanian used real value added (which is based on real revenue) rather than costs as their dependent variable. Thus, their dependent measure confounds demand-side issues with supply-side issues. See discussion in Section 4.1.4 "Balasubramanian & Lieberman, 2010."

#	Peer Reviewer	Peer Reviewer Comment	Response
28	Balasubramanian	Consider Haunschild and Rhee (2004).	We gave this article a cursory review and added a summary to Appendix C, "Summaries of Articles Related to the Mobile Source Sector that Received a Cursory Review."

Literature Review – Knowledge Persistence and Depreciation (Section 4.2)

#	Peer Reviewer	Comment	Response
29	Lieberman	This section does a good job of characterizing studies of the learning effect that have considered knowledge depreciation. One confusing element in this section is that some of the depreciation rates are monthly and others are annual. On pages 27 and 28, for example, the text might clarify that Benkard and Argote's estimates are monthly rates of depreciation (although the figures are converted to an annual basis in Table 3).	We added this comment to a footnote in Section 4.2, "Knowledge Persistence and Depreciation." We presented the annual depreciation rates in the text. We added a footnote to each converted depreciation parameter, which would (1) explain that we are showing the converted value(s), (2) show the original value(s) used in the article, and (3) refer the reader to Table 3, where we show the conversion.
30	Syverson	To the extent that one objective of the study is to identify the expected pace at which mobile source manufacturing productivity should improve with production experience, though, it seems to me that what matters in the end is the net effect of learning and depreciation rather than the gross learning rate. I recognize the gross-versus-net distinction might not be easy to quantitatively reconcile. Therefore it might not be possible to derive a bottom-line net learning rate parameter that is as comparable and applicable as the gross parameter the study reports now. However, it does seem prudent to at least discuss the net-versus-gross distinction and how it might matter when applying the findings of the report to practical settings. I realize that the study argues that mobile source manufacturing has several properties (production typically is conducted at an even rate, learning is often embedded in technology and routines, and the sector experiences relatively modest worker turnover) that make it likely that depreciation would tend to be on the low end of estimates in the literature. This does not seem unreasonable. However, arguing that	See discussion in Section 5, "Responses to Peer Reviewer Comments Related to the Analysis."

#	Peer Reviewer	Comment	Response
		these effects are likely to be smaller than usual does not necessarily imply depreciation is likely to be zero. Again, there might not be any easy practical alternative here in terms of quantitative reports, but it is worth discussing the issue.	

Literature Review – Knowledge Transfer and Spillovers (Section 4.3)

#	Peer Reviewer	Peer Reviewer Comment	Response
31	Lieberman	This section is effective in describing research findings relating to knowledge transfer across organizational units (e.g., additional shifts, new models) within a given firm. However, the section ignores the existing literature on knowledge transfer and spillovers across firms (except for very brief mention in Footnote 5). This literature on inter-firm spillover of learning is fairly extensive, although the evidence is based mostly on studies using data outside the mobile source sector.	In the introduction of Section 4.3, we clarified that distinguishing components of learning was not an objective of our report; therefore, the studies do not cover all components of knowledge transfer. In addition, we added this comment to a footnote in Section 4.3.

Literature Review – Location of Organizational Knowledge (Section 4.4)

#	Peer Reviewer	Peer Reviewer Comment	Response
32	Lieberman	This section is informative and well done. I think it would be helpful to provide some of this material earlier in the report—specifically, to make it clear that learning and knowledge can be embedded in people, in organizational routines, or in technology/physical capital.	We discuss that learning and knowledge can be embedded in people, routines, and technology in the third paragraph of the introduction to Section 3, "Summary of Results and Recommendations." We also added a discussion in our summary of the 18 articles in Section 3.3.

Literature Review – The Specification and Aggregation of Learning (Previously Section 4.5)

#	Peer Reviewer	Peer Reviewer Comment	Response
33	Lieberman	Section 4.5 does not truly serve a standalone function; rather, it seems to be a placeholder to summarize three studies that were otherwise hard to classify. Perhaps the section should take a broader perspective, summing up many of the conclusions of the previous sections that relate to the specification and aggregation of learning.	We agreed that Section 4.5 did not serve an important function. Therefore, we reviewed the three articles, Bahk and Gort (1993), Laitner and Sanstad (2004) and Levin (2000), to decide whether they were correctly categorized. We decided to move Bahk and Gort to Section 4.4 and to re-categorize the Laitner and Sanstad and Levin articles to those that receive a cursory review. The Bahk and Gort (1993) article focuses on disaggregating learning into organizational learning, capital learning, and labor learning. We moved the discussion of this article to Section 4.4, “Location of Organizational Learning.” We moved the Levin (2000) article to Appendix C and removed the discussion from the body of the report. We retained the discussion about whether time is an important source of improvement in the quality of cars (as opposed to cumulative output). We moved Laitner and Sanstad (2004) to the category of articles that received a cursory review. Because the article dealt with learning and general, it is not featured in Appendix C. We re-categorized this article mainly because it is unrelated to the mobile source sector, it is based on projections rather than actual data, and it is not focused on learning from the producer’s point of view. We added a footnote to Section 4.1, “Sources of Learning Variation” to point out that learning from the consumer’s point of view is another interesting type of learning. We moved Levin (2000) to Appendix

#	Peer Reviewer	Peer Reviewer Comment	Response
			C and removed the discussion from the body of the report. We retained the discussion about whether time is an important source of improvement in the quality of cars (as opposed to cumulative output).
34	Syverson	Considering adding Hendel and Spiegel (American Economic Journal: Applied Economics, Jan. 2014)	We gave this article a cursory review; however, it will not be included in Appendix C because is not related to the mobile source sector. In the response to peer reviewers, we will explain why we choose not to give the article a detailed review (e.g., it may not be representative because it is a single for that produces a single product, they may be on the flat portion of the learning curve, small increases in learning may be offset by small increases in forgetting, learning may be embedded in technology, learning may be insignificant because a time trend was included).
35	Syverson	I struggled to understand how the work of Laitner and Sanstad (2004) fit into the discussion. I realize that there might be learning about products among consumers, but it wasn't exactly clear to me from the description of their paper how this would influence supply-side learning. My best guess of the story is that demand-side learning affects the equilibrium quantity of a product, and that can change how quickly experience is accumulated on the supply side. If that is correct, though, then it is less clear to me that one would necessarily want to purge demand-side influences from learning estimation, as asserted in the price-as-an-outcome issue discussed above. Is there a fundamental difference between that point and the Laitner and Sanstad (2004) analysis?	We re-categorized the Laitner and Sanstad article to group of articles receiving a cursory review. Because the article deals with learning in general, we do not feature the article in Appendix C. The article does not explain how demand-side learning reduces costs. However, we would argue that our decision to discount articles that us price as an outcome variable is still valid. If Syverson's guess is accurate, price may be viable as an outcome variable if one could control for things such as firm strategy and market conditions. However, data related to a firm's strategy would likely not be available and therefore, it would be difficult to parse out the relationship between price and learning on the demand or supply side.

Literature Review – Application of the Learning Curve (Previously Section 4.6)

#	Peer Reviewer	Peer Reviewer Comment	Response
36	Lieberman	The studies summarized in the section are quite diverse. Nevertheless, it seems appropriate to have a concluding section to consider these studies. It is striking that Nykvist and Nilsson's (2015) survey found learning rates for production of automotive Li-ion battery packs to be substantially smaller than the 84.3% progress ratio that the EPA report proposes for cost forecasting in the mobile source sector. It would be informative to consider possible sources of this large discrepancy in learning rates between Li-ion battery manufacturing and transportation equipment final assembly.	We agree that Nykvist and Nilsson estimated a learning curve rate of 9% for the Li-ion battery industry generally and 6% for the market-leading manufacturers. However, we disagree that this is evidence of a large discrepancy in learning rates between Li-ion battery manufacturing and transportation equipment final assembly. The authors note that those learning rates are estimated using data from 2007 to 2014. However, they also note that while industry-wide average costs declined by about 14% annually from 2007 to 2014, costs are expected to decline 8% annually in the future ("Hence, we believe that the 8% annual cost decline for market-leading actors is more likely to represent the probable future cost improvement for Li-ion battery packs in BEV."). When this projected cost decrease is taken into account, the results are not dissimilar to the 84.3% progress ratio estimated in this report. Specifically, in early years, the classic progress ratio-based cost reductions reflected in the 84.3% progress ratio result in more rapid cost declines, but those declines flatten out due to the logarithmic nature of the calculations. An 8% annual rate of cost reduction results in less rapid cost declines, but those declines remain at 8% per year going forward such that, after 11 years, costs are actually lower using the 8% annual rate of decline. As explained in Section 3.1 of this report, with respect to the form of the learning curve, the preponderance of studies support a logarithmic relationship over a linear relationship. This suggests that, while the two rates are similar in this case, the logarithmic relationship is more

			appropriate for use in cost estimations. See attachment D1 to this appendix for the discussion of the Nykvist and Nilsson study that was included in EPA's July 2016 Draft Technical Assessment Report

Typographic Errors and Other Minor Corrections

#	Peer Reviewer	Peer Reviewer Comment	Response
37	Lieberman	In the *title of Summary Table 1*, "Progress Rations" should be Progress Ratios."	Update to body of EPA Report (by EPA)
38	Lieberman	*Summary and Background, page 3*. In the middle paragraph, "for each doubling of production volume" should be "for each doubling of cumulative production volume." In the sentence that follows, "it was assumed that production volumes would have doubled" should be "it was assumed that cumulative production volumes would have doubled".	Update to body of EPA Report (by EPA)
39	Lieberman/ Syverson	Page 19. "In error! Reference source not found" is a typographical error. From the context it appears to be a reference to Table 2.	We updated the link to "Table 2".
40	Syverson	There is a missing closed parenthesis in the first sentence of EPA summary.	Update to body of EPA Report (by EPA)
41	Syverson	On page 49 in the appendix, the "review of the literature" progress ratio is cited as 83%, but the estimate given in the main body of the review is 84%.	We updated the calculations in Appendix A to 84% to be consistent with our recommendation.
42	Syverson	The Levitt, List, and Syverson study is cited as being published in both 2012 and 2013 in different locations.	We replaced the study's publication dates with 2013.
43	Syverson	Also, on page 38, Levitt, List, and Syverson are described as studying the repair rate as an outcome variable rather than the defect rate.	This discussion was removed from the report. However, with the statement, "Levin's results contrast with the findings of Levitt et al. (2013) who also examined quality learning curves and found that cumulative output was a better predictor of the outcome variable, the repair rate, than time," we intended to convey that Levin used repair rate as the outcome variable—not Levitt et al.

Attachment D1. Excerpt from EPA’s Draft Technical Assessment Report: Midterm Evaluation of Light-Duty Vehicle Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards for Model Years 2022-2025.

The following is an excerpt from EPA’s July 2016 Draft Technical Assessment Report, which is provided in connection with a response to a peer reviewer’s comments regarding the estimated learning rates in an article by Nykvist and Nilsson (2015).

historical average). The researchers also suggested that the primary difficulty imposed by such fluctuations would be felt by cell manufacturers in maintaining profit margins, rather than by vehicle manufacturers or consumers.

5.2.4.4.9 Evaluation of 2012 FRM Battery Cost Projections

In the 2012 FRM, the agencies adopted a bottom-up, bill-of-materials approach to projecting the future DMC of xEV batteries by using the ANL BatPaC battery cost model.[137] As discussed in the Technical Support Document (TSD)[136] accompanying the 2012 FRM, battery pack costs projected by this model were shown to compare favorably with cost projections provided by suppliers and OEMs that were interviewed during development of the rule. In the 2015 NAS report (Finding 4.4, p. 4-43), the committee found that "the battery cost estimates used by the agencies are broadly accurate," providing further support for the use of this model.

At the time of the FRM, few public sources were available to further validate these projections. Since that time, several sources have emerged that provide additional information on the evolution of battery costs since the FRM and potential future trends.

In 2015, a peer-reviewed journal article (Nykvist and Nilsson, 2015) appeared that provides a comprehensive review of over 80 public sources of battery cost projections for BEVs.[142] Based on a statistical analysis of these estimates, it was shown that industry cost estimates for lithium-ion batteries for BEVs have declined 14 percent annually between 2007 and 2014, and that pack costs applicable to leading BEV manufacturers have followed a cost reduction curve of about 8 percent per year, with a learning rate of between 6 percent and 9 percent. The authors concluded that the battery costs experienced by market leading OEMs are significantly lower than previously predicted, and that battery costs may be expected to continue declining.

Figure 5.37 compares the full population of cost estimates reviewed by Nykvist and Nilsson to the battery pack cost projections of the 2012 FRM analysis. Because BatPaC does not produce cost estimates for multiple years, the 2012 FRM analysis applied a learning curve to generate costs for the years 2017 through 2025, with BatPaC output costs assigned to the year 2025. The learning-adjusted FRM costs shown in the figure include those for PHEV40, EV75, EV100 and EV150, which have relatively large capacities similar to those likely included in the review. The plot shows that the battery costs projected in the 2012 FRM fit well with the reviewed estimates, and lie on a similar cost reduction curve.

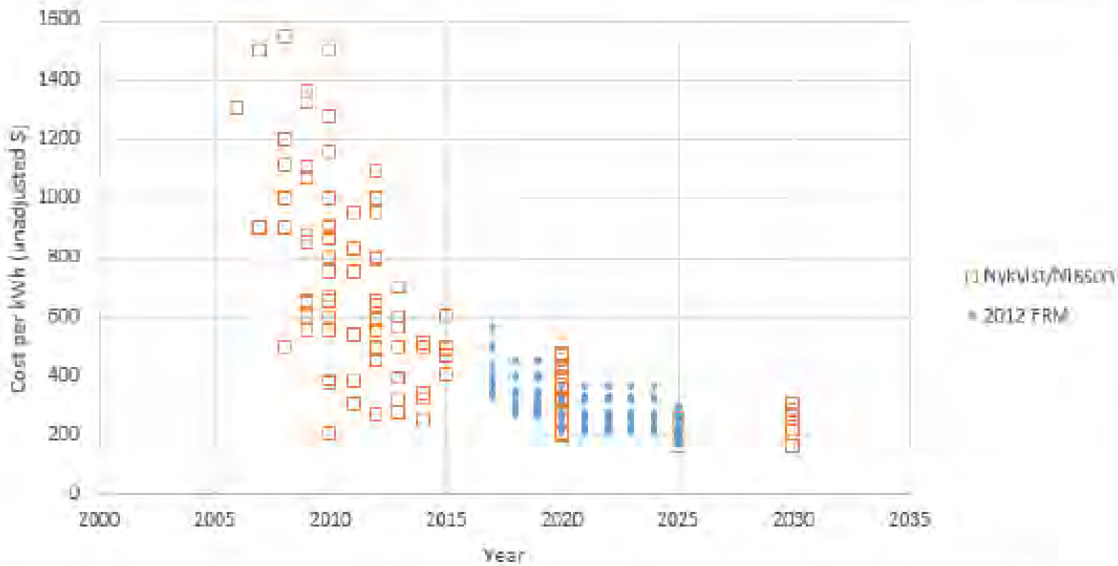

Figure 5.37 Comparison of 2012 FRM Projected Battery Cost Per kWh to Estimates Reviewed by Nykvist & Nilsson

Cost estimates and projections are most useful when they can be validated by comparison to actual costs. Unfortunately, information about actual battery costs paid by manufacturers for production vehicles is rarely disclosed publicly. However, in October 2015, General Motors publicly commented on its battery costs for the Chevy Bolt EV, providing an opportunity to evaluate the FRM projections of BEV battery costs.

At the General Motors Global Business Conference on Oct. 1, General Motors described to an investor audience its current and projected cost per kWh (on a cell basis) for battery cells for the Chevy Bolt EV. Citing partnership with cell manufacturer LG Chem, Executive Vice President of Global Product Development Mark Reuss stated, "When we launch the Bolt, we will have a cost per kWh of $145, and eventually we will get our cost down to about $100. We believe we will have the lowest cell cost with much less capital and volume dependency."[337] An accompanying chart shows the $145 cost continuing to 2019, dropping to $120 per kWh in 2020 and to $100 per kWh in 2022.[338,339]

It is important to note that the costs described above are cell-level costs and not pack-level costs. To compare them to the pack-level costs projected by the agencies requires converting them to that basis using an appropriate methodology. Also, although the context of the announcement suggests that the costs are comparable to a direct manufacturing cost, their exact basis is unknown. Although these factors introduce some uncertainty in comparing the announced costs to the FRM projections, a qualified comparison is possible.

Several sources exist that suggest a cost conversion factor from cell-level costs to pack-level costs for lithium-ion batteries.[340,260,248,341,342,343] These are summarized in Table 5.6. Most of these sources suggest a conversion factor of about 1.25 to 1.4 may be appropriate.

Table 5.6 also shows two estimates derived from the ANL BatPaC model for a liquid-cooled BEV-sized pack at a production volume of 50,000 to 100,000. Outputs from this model suggest that the ratio of pack-level cost to cell-level cost for the pack format modeled by BatPaC may range from about 1.5 for a 16 kWh pack to about 1.3 for a 32 kWh pack, and continuing to decrease for larger pack capacities.

Table 5.6 Examples of Conversion Factors for Cell Costs to Pack Costs

Source	Low	High
Kalhammer et al.[340]	1.24	1.4
Element Energy[269]	1.6	1.85
Konekamp[248]	1.29[BB]	
USABC[341]	1.25[CC]	
Tataria/Lopez[342]	1.26[DD]	
Keller[343]	1.2[EE]	
BatPaC, 16 kWh	1.5	
BatPaC, 32 kWh	1.3	

On the basis of the BatPaC-derived ratios of 1.3 to 1.5, the 2015-2019 cell-level figure of \$145 per kWh would translate to approximately \$190 to \$220 per kWh on a pack level. The future projections of \$120 and \$100 per cell kWh in 2020 and 2022 would translate to approximately \$156-\$180 per kWh and \$130-\$150 per kWh at the pack level, respectively.

On this pack-converted basis the GM cell costs agree well with the BatPaC cost projections that the 2012 FRM analysis applied to 2025. Table 5.7 summarizes the estimated pack-level equivalents of the cell costs disclosed by GM and compares them to the EV150 pack-level BatPaC output costs of the FRM analysis. The pack-converted GM projection for 2020, at \$156-\$180 per kWh, compares well to the FRM BatPaC output costs for EV150[FF] for 2025, which ranged from \$160 to \$175 per kWh (at 450,000 units annual volume). The pack-converted GM projection for 2022 at \$130-\$150 per kWh is significantly lower than the agencies' projection for 2025. This suggests that the 2012 FRM cost projections, at least for EV150, may have been quite conservative.

Table 5.7 Comparison of GM/LGChem Pack-Converted Cell Costs to FRM EV150 Pack Cost

		Pack Cost/kWh (2015$)	
Source of Estimate	Year Applicable	Low	High
EV150 in FRM	**2025**	**\$160**	**\$175**
GM/LG Global Business Conference	2015-2019	\$190	\$220
	2020	**\$156**	**\$180**
	2022	\$130	\$150

Figure 5.38 compares the pack-converted GM costs to the year-by-year learning-adjusted costs used in the 2012 FRM for Small, Standard, and Large Car EV150. It can be seen that the

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[BB] Cell cost = 620 Euros*16 modules = 9,920 Euros; pack cost = 12,800 Euros; 12,800/9,920 = 1.29.

[CC] USABC 2020 goals for advanced EV batteries cite a cost of \$125/kWh at pack level and \$100/kWh at cell level = 1.25.

[DD] For a 40 kWh pack, cell costs estimated at \$258/kWh; pack-related costs at \$2,626, or \$66 per kWh; (258+66)/258 = 1.26.

[EE] Cites one goal of 21st Century Truck Partnership as "Cost of overall battery pack should not exceed cost of the cells by more than 20% by 2016" (slide 6).

[FF] The Chevy Bolt is anticipated to offer a 200-mile driving range, potentially comparable to the real-world 150-mile range of the EV150 that the agencies modeled in the FRM.

range of the pack-converted GM costs is lower than the costs predicted by the 2012 FRM analysis.

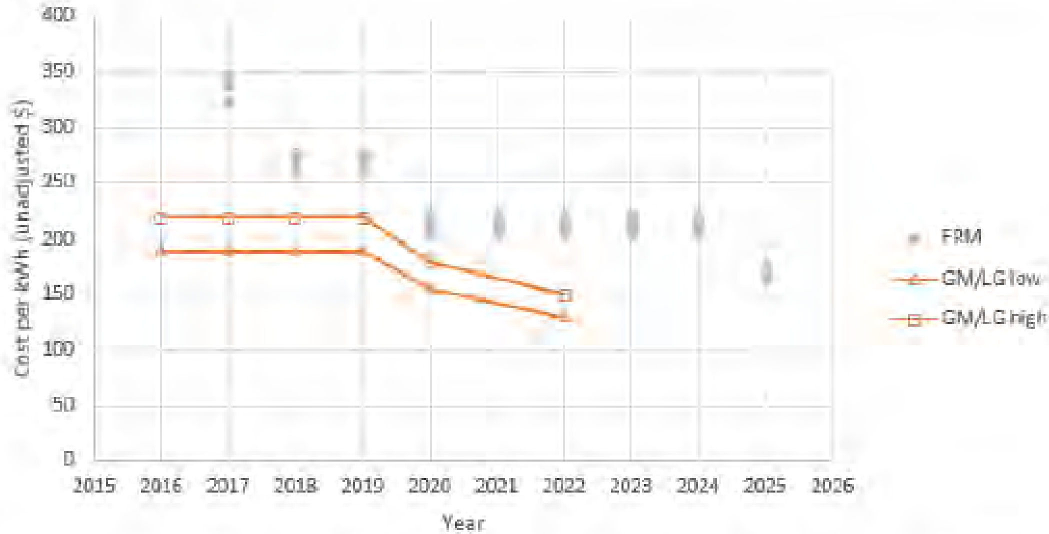

Figure 5.38 Comparison of Estimated GM/LG Pack-Level Costs to 2012 FRM Estimates for EV150

At the time of the FRM, the agencies' battery cost estimates appeared to be lower than costs being reported by many suppliers and OEMs at the time, and also lower than some independent estimates said to be applicable to the time frame of the rule. The agencies chose to place confidence in the peer-reviewed ANL BatPaC model due to its rigorous, bottom-up approach to battery pack costing, and the expertise of leading battery research scientists that contributed to its development. The comparisons described above suggest that this approach was effective and may in fact have been conservative not only with respect to characterizing the pace of reductions in battery cost that have taken place in the time since the FRM but also to projecting future costs for the 2020-2025 time frame. Up to and including the development of this Draft TAR analysis, the agencies have continued to invest significant resources into understanding developments and emerging trends in battery technologies so that these critically important projections of xEV battery cost may be as reliable as possible.

While other public examples of battery costs to manufacturers remain elusive, several suppliers and manufacturers have made battery-related product announcements since the FRM. Some of these include information suggestive of battery costs or pricing. Some manufacturers have published pricing for battery replacement parts or upgrades available to authorized service providers. Others have offered different options, such as battery size or purchase method, the relative pricing of which may suggest a relationship to battery cost. Finally, stand-alone non-automotive Li-ion battery packs are beginning to become available to end users and their pricing may be informative. While the agencies recognize that the pricing of these early-stage product offerings may be subsidized by their manufacturers for competitive and marketing reasons, these announcements may still be relevant to understanding the evolution of battery pack costs as these products increase their presence in the market.

In 2013-2014, Tesla Motors offered the Model S in two battery pack sizes, 60 kWh and 85 kWh, at retail prices of around $69,900 and $79,900, respectively. Assuming no content difference between the two versions, the retail price differential would suggest a battery cost of $10,000 / 25 kWh = $400/kWh. An alternate analysis presented by Nykvist et al.[344] subtracts the estimated value of added content found in the 85 kWh version (Supercharger, premium tires, and associated markup), resulting in a net price difference of $8,500 or $340 per kWh.

In July 2014, Nissan announced the replacement cost of a 24-kWh battery for the Nissan Leaf at $5499 with core return, which amounts to about $229/kWh net. Although Nissan requires return of the original battery (core), a $1000 credit is then applied for the core, suggesting a full retail price of $6499, or $271/kWh.[345,346,347] Later the same month, Nissan followed up by pointing out that the quoted price is in fact subsidized by Nissan, although they declined to report the amount of subsidy or the actual manufacturing cost.[348] Nissan does not allow purchase of the battery except as a Leaf battery replacement.

In 2015, an independent vendor of OEM parts listed the 2011 Chevy Volt battery pack at $10,208 list price, discounted to $7,228, with no mention of core exchange. Assuming a 16 kWh capacity, these prices would value the battery at $638/kWh and $452/kWh, respectively. Although the product was listed and priced by the vendor, it was on restriction from ordering for reasons that remain unclear.[349,350]

In January 2015, it was reported that the MSRP for a BMW i3 battery pack module was listed at $1,805.89, each module being 2.7 kWh (21.6 kWh total divided by 8 modules). This module price would equate to $669/kWh. A specific dealer was reported to be offering the module at a price of $1715.60, or $635/kWh.[351]

In September 2015, Tesla announced the price for a range-increasing battery pack upgrade for the Tesla Roadster at $29,000, including installation and logistics. Tesla indicated that the quoted price is meant to be equal to Tesla's expected cost in providing the pack, and disclaimed any intention to make a profit. Tesla also indicated that the price per kWh is higher than for a Model S battery due to the low volume production expected for the Roadster upgrade pack (only approximately 2,500 Roadsters were produced). Tesla did not list the kWh capacity of the upgrade pack, but describes it as having approximately 40 percent more energy capacity than the original Roadster pack, which is commonly listed as 56 kWh. This suggests that Tesla's cost for low volume production of this pack is around $29,000/(56*1.4) = $370 per kWh.[352] In October 2015, Tesla further announced that the Roadster upgrade packs would be provided through a partnership with LG Chem.[353] This suggests that the price of the pack may not reflect anticipated savings from the Panasonic-Tesla "Gigafactory" partnership.

In August 2013, the Smart ED was offered with a 17.6 kWh battery, with the option to either purchase the battery with the car, or lease it separately. The vehicle price was $5,010 lower without the battery when the battery was leased at a price of $80/mo. If the $5,010 differential was taken to represent the incremental cost of the battery, it would value the battery at $285/kWh. Of course, the present value of the lease payments would also contribute value to the transaction, and it is possible that marketing considerations could also be represented in the pricing.[354,355,356]

In September 2015, Nissan announced pricing in the UK for the 2016 Nissan Leaf. In a press release from Nissan, equivalent versions of the Leaf having a 30 kWh pack instead of a 24 kWh pack were priced at a difference of 1,600 British pounds. This would amount to approximately 267 British pounds per kWh, or U.S. $411 per kWh (assuming an exchange rate of 1.54 U.S. dollars per pound). It should be noted, however, that although the two versions of the pack appear to be designed to install into the same footprint and volume, any cost comparison is potentially complicated by differences in chemistry and construction of the two versions.[357]

In 2014, Tesla Motors began construction of a so-called "Gigafactory" in Nevada in partnership with Panasonic. This factory is commonly cited by Tesla as enabling a potential 30 percent reduction in battery pack costs from the levels Tesla currently pays. According to one analysis,[358] Tesla's current cost is estimated at about $274 per kWh. A 30 percent reduction on that figure would bring costs to about $192 per kWh.

In April 2015, Tesla announced a home battery pack product called Powerwall, pricing a 7 kWh version at $3,000 ($428/kWh) and a 10 kWh version at $3,500 ($350/kWh). Although designed for stationary home use, the pack design bears similarities to automotive packs, being liquid-cooled and using similar chemistries. The 7 kWh version employs NMC chemistry similar to many production BEVs, while the 10 kWh version employs the NCA chemistry like the Tesla Model S. Tesla also announced a similar product called Powerpack for commercial use. Powerpack was said to be priced at $25,000 for 100 kWh capacity, or $250/kWh. These products are expected to take advantage of much of the cell output of the Gigafactory, suggesting that these products may be priced in anticipation of the cost reductions it is expected to achieve. Table 5.8 summarizes the estimated cost or pricing information derived from the foregoing examples.

Table 5.8 Summary of Published Evidence of Battery Pack Cost and Pricing

		Pack Cost or Price per kWh	
Source of Evidence	Year Applicable	High	Low
Tesla Model S 60 kWh vs 85 kWh comparison	2013-2014	$340	$400
Nissan 24 kWh replacement pricing	2015	$229	$271
Vendor pricing for 2011 Volt pack	2015	$432	$638
Dealer pricing for BMW i3 module	2015	$635	$669
Tesla Roadster upgrade pricing	2015	$370	
Smart ED lease vs buy pricing	2013	$285	
Nissan UK price differential 30 kWh vs 24 kWh	2015	$411	
Tesla Lux Research estimate	2014	$274	
Tesla Lux Research estimate modified by Gigafactory	2017	$192	
Tesla Powerwall	2015-2016	$350	$428
Tesla Powerpack	2015-2016	$250	

It is important to remember that the figures derived from these examples should be interpreted with caution. The agencies' cost projections represent direct manufacturing costs and not retail pricing. Also, as previously noted, retail pricing of these early-stage product offerings may be subsidized by their manufacturers and may reflect competitive and marketing considerations that further obscure their true manufacturing cost. Furthermore, some of the estimates are derived from full-product comparisons that may or may not accurately represent the battery portion of the comparison. It should also be noted that the examples presented here represent current pricing, while the FRM applies its BatPaC cost projections to the year 2025.

On the other hand, the existence of these examples shows that the industry has progressed considerably since the FRM, when such examples were almost entirely unknown. The identification and packaging of specific battery products for upgrade, replacement or standalone use is a significant development and suggests that the industry is continuing to gain in maturity and is growing along multiple paths. The establishment of MSRPs for many of these products also suggests that manufacturers are beginning to gain confidence in their understanding of the cost structure of battery products. The examples and estimates derived from this analysis, even if approximate, can serve to ground the various cost estimates and projections that have previously been the primary source of battery costing information (and will continue to play an important role going forward).

5.2.4.5 Fuel Cell Electric Vehicles

5.2.4.5.1 Introduction to FCEVs

Fuel Cell Electric Vehicles (FCEVs) are another potential technology option for implementing electrified drive to achieve zero tailpipe emissions, like the BEV technology presented in Section 5.2.4.3.5. Like BEVs, FCEVs use electricity to turn electric motors onboard the vehicle that provide the motive power for driving. However, unlike a BEV, the FCEV also produces this power onboard. It achieves this by harnessing the energy produced in an electrochemical reaction that combines hydrogen and oxygen to form water. This process occurs within the fuel cell itself, a device that shares a basic structure with batteries; namely, it consists primarily of an anode, a dividing electrolyte, and a cathode. Hydrogen from an onboard tank enters the fuel cell's anode and is separated into its constituent electron and proton. The electron is directed to an external circuit, where it ultimately provides power to the electric motors driving the wheels. The proton is transferred across the fuel cell's electrolyte membrane to the cathode, where it combines with oxygen from air entering the cathode and electrons returning from the external circuit to form water. Thus, the basic reaction in the fuel cell is $H_2 + ½O_2 \rightarrow H_2O$, with usable electric power (and some amount of heat) produced in the process.

State and national policies have increasingly adopted the perspective that FCEV and BEV technologies will be complementary vehicle technologies that will likely both be needed in order to achieve long-term GHG reduction goals. Well-to-wheel GHG emissions for FCEVs and BEVs vary depending on the method of production for their various fuels (electricity for BEVs and hydrogen for FCEVs), but both technologies hold promise for significant reduction below current and projected future ICE vehicle GHG emission rates (see Chapter 9, Infrastructure Assessment for a more complete presentation of GHG emissions from hydrogen production). Hydrogen energy storage, the conversion of electrical energy into hydrogen gas through the process of electrolysis, has recently gained significant attention for its potential to enable increased renewable penetration in the electric grid, thus potentially playing a significant role in decarbonizing multiple industries in the full US energy system. Although there is potential for FCEVs to play a significant role in reducing GHG emissions, the technology is still relatively new (the first mass-produced vehicles entered the market in 2014) and costs have historically been higher than other options. For this reason, FCEVs were not included in the projections of the future vehicle fleet in the 2012 FRM.

The 2010 Technical Assessment Report (TAR) covered developments and state-of-the-art technology for the FCEV at the time. Since then, researchers and developers in government, academia, and industry have continued to advance the technology's performance capability and

Appendix E. Peer Review Report

RTI Project Number
0213244.004.014

Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources Peer Review

Peer Review Report

May 2016

Prepared for

U.S. Environmental Protection Agency
Office of Transportation and Air Quality
Office of Air and Radiation (US EPA OAR/OTAQ)
2000 Traverwood Dr.
Ann Arbor, MI 48105

Prepared by

RTI International
3040 E. Cornwallis Road
Research Triangle Park, NC 27709

CONTENTS

SECTION 1
INTRODUCTION

The Office of Transportation and Air Quality (OTAQ) within the U.S. Environmental Protection Agency (EPA) has requested a peer review of "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources" developed for EPA by ICF International. The purpose of the study is to develop a single compendium study on industrial learning in general and the mobile source sector specifically that the Agency can use as the basis for accounting for learning effects in the cost analyses developed for regulatory and other actions. The study provides an assessment of manufacturing learning through analysis of published studies and literature and, using that information, estimates a progress ratio (learning rate) for the mobile source sector.

RTI International (RTI), an independent contractor, was contracted by OTAQ to facilitate a peer review of the study. The peer review was carried out based on the *EPA Science Policy Council Peer Review Handbook, 4th Edition* (U.S. EPA, 2015; henceforth referred to as the Peer Review Handbook). The peer review was conducted to ensure that the learning study can be considered a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically. Three recognized experts in learning effects were engaged to review the learning study and provide feedback on: (1) clarity of the presentation, (2) overall approach and methodology, (3) appropriateness of the studies included and other inputs, (4) data analyses conducted, and (5) appropriateness of the conclusions.

This report includes a description of the peer review process, a summary of the peer review reports, and the individual peer reviewer reports. In addition, all materials provided to the peer reviewers to support the review, such as the panel charge and the technical work product, as well as peer reviewer resumes and a conflict-of-interest (COI) disclosure form, are provided in the appendices.

SECTION 2
PEER REVIEW PROCESS

In December 2015, EPA's OTAQ requested that RTI facilitate a peer review of the report *Cost Reduction through Learning in Manufacturing Industries and In the Manufacture of Mobile Sources*. RTI managed the peer review independently and according to guidelines set forth in EPA's Peer Review Handbook (U.S. EPA, 2015). RTI initiated the process of identifying and selecting three peer reviewers in January 2016 and completed the peer review process in April 2016.

To identify qualified candidates for consideration, RTI identified 12 candidates based on recommendations from EPA; a literature review; and an online resources investigation. Qualified candidates were those with knowledge of learning effects and expertise in mobile sources and manufacturing sectors. Per instructions from EPA, RTI aimed to select three reviewers from the candidate pool based on all of the following criteria:

- Their expertise, knowledge, and experience;
- Their adherence to the COI guidance in the EPA's Peer Review Handbook (U.S., EPA, 2015); and,
- The diversity of their relevant scientific and technical perspectives.

Three candidates were highlighted based on recommendations from subject matter experts and those with relevant expertise. RTI contacted these candidates to ascertain their availability and potential COI. Each candidate completed a COI disclosure form to identify any and all real or perceived COI or bias, including funding sources, employment, public statements, and other areas of potential conflict, in accordance with EPA's Peer Review Handbook (U.S. EPA, 2015). A template of the COI disclosure form completed by the candidates is included in **Appendix A**. RTI staff supporting the peer review also underwent a COI investigation to corroborate the independence and a lack of bias across all components of the peer review.

Based on the candidates' availability and qualifications, the information provided in the completed COI disclosure forms, and an independent COI investigation conducted by RTI staff, RTI selected the following three candidates:

- Marvin Lieberman, Ph.D., University of California, Los Angeles (UCLA) Anderson School of Management
- Natarajan Balasubramanian, Ph.D., Whitman School of Management, Syracuse University
- Chad Syverson, Ph.D., University of Chicago Booth School of Business.

All three selected peer reviewers reported no COI on the disclosure form and were identified to be in compliance with EPA's Peer Review Handbook (U.S. EPA, 2015). EPA reviewed and approved the list of candidates selected by RTI as appropriate choices from the candidate pool. Copies of the selected candidate resumes are included in **Appendix B** of this report.

RTI provided the peer reviewers with the following materials to guide the evaluations:

- EPA-developed Peer Review Charge (see **Appendix C**)
- Technical Work Product *Cost Reduction through Learning In Manufacturing Industries and In the Manufacture of Mobile Sources* (hereafter referred to as the EPA Report)

The peer reviewers met with EPA once by conference call in March 2016 to give peer reviewers the opportunity to ask questions about the context of the study. Peer reviewer questions and answers regarding the charge are included in **Appendix D**.

RTI received the review reports and cover letters that stated the reviewer's name, the name and address of the reviewer's organization, the documents that were received and reviewed by the reviewer, and a statement of any real or perceived COI from each of the reviewers, and forwarded the reports to EPA by the requested dates. The review reports included the responses to the charge questions and any additional comments or recommendations. The cover letters and the review reports are included in **Appendix E** of this report.

Peer reviewers were provided with an honorarium of $4000 to compensate for their effort. The following sections provide the findings of the peer review.

SECTION 3
SUMMARY OF FINDINGS

This section provides a summary of the comments received from the three reviewers: Marvin Lieberman (UCLA), Natarajan Balasubramanian (Syracuse University), and Chad Syverson (University of Chicago). The charge directed peer reviewers to evaluate the EPA Report using the following five criteria: (1) clarity of the presentation, (2) overall approach and methodology, (3) appropriateness of the studies included and other inputs, (4) data analyses conducted, and (5) appropriateness of the conclusions. The remaining summary of comments have been organized into sections according to these criteria, and other comments have been included as the final section. Please see **Appendix E** for the complete reports from each peer reviewer.

3.1 Overview of the Peer Reviewer Comments

Overall, the reviewers found the EPA Report to be well-executed, with a reasonable approach, inputs, and conclusions. Comments received on the overall report include the following:

- "The overall conclusion that learning-by-doing occurs in the mobile source sector is well-founded and largely indisputable" (Dr. Balasubramanian)
- "On balance, the study is a very fine review of the literature on learning by doing in general, but especially with regard to its manifestation in manufacturing operations during the past few decades….The report does achieve the intended goal of being a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically" (Dr. Syverson)
- "I find the report to be comprehensive, and I believe it does a good job of characterizing the rates of learning typically found in transportation equipment manufacturing plants" (Dr. Lieberman).

Dr. Lieberman added that "Dr. Linda Argote of Carnegie Mellon University, the Subject Matter Expert for the report, is widely regarded as the world expert on industrial learning curves, having published numerous research studies in this topic area and a major book."

Reviewer comments included technical suggestions, such as recommendations to improve methods transparency, as well as requests for clarification, three additional studies for consideration, and a few clerical edits.

3.2 Clarity of the Presentation

The reviewers felt the overall presentation and organization of the report was generally clear and easy to follow. Comments provided from the reviewers to further improve clarity included the following:

- Dr. Balasubramanian recommended that the report explicitly state the objectives of the report and elaborate the summary of the literature review. In addition, Dr. Balasubramanian suggested replacing the term “best estimate” to avoid confusion with the econometric definition.
- Dr. Syverson requested additional context around the Laitner and Sanstad (2004) analysis and how it might influence supply-side learning.
- Dr. Lieberman recommended that the organizational knowledge discussed in Section 9 would better inform the reader at an earlier location in the report. He also noted an inconsistency among the reported temporal basis of the depreciation rates in Section 4.4 as a source of confusion.

3.3 Overall Approach and Methodology

Comments regarding the approach and methodology were generally positive; however, additional clarification was recommended regarding the approaches and assumptions made in the report. All reviewers provided comments on the method of estimating the progress ratios and suggested that the report clarify the standard error calculation methods. Drs. Lieberman and Balasubramanian discussed various methods that might be used to compute the progress ratio and variations that may occur across industries, but stated that the estimated ratio is justified and reasonable.

Dr. Balasubramanian recommended a more detailed summary of the literature review to accompany the table in Section 3.3 of the report. Dr. Balasubramanian also suggested a detailed discussion about the report’s use of cumulative output as a predictor and the variation and uncertainty associated with learning-by-doing, including the potential effect of other factors. Furthermore, the peer reviewer recommended greater context regarding the five highlighted studies in the discussion of the weighted-average progress ratio to improve the transparency of the approach. Additionally, Dr. Balasubramanian stated that the overview of the report endeavors to provide an analysis of the learning effect by industry but ultimately provides one estimate for the entire sector. He suggested that using the means of the subgroups rather than the mean of the group as a whole may be useful if and when estimates become available.

Dr. Lieberman suggested that the average value is useful for forecasting purposes, but cautioned against any implication that the estimated progress ratio is a precise and universal standard due to variation across products, plants, and processes in the sector. Dr. Lieberman also suggested that the report recognize the emphasis on cumulative output as a predictor.

Dr. Syverson stated that the consistency across progress ratio estimates is striking, but differences across industry and outcome measures cannot be ruled out with only five studies. The reviewer recommended further study and discussion where possible. Additionally, Dr. Syverson recommended further inquiry into the net versus gross rate of learning and depreciation to help determine whether there is variation in when and how to apply a learning effect.

3.4 Appropriateness of the Studies Included and Other Inputs

All three peer reviewers stated that the literature review is comprehensive. Each peer reviewer identified an additional paper or article that may add insight to the literature review provided in the report, but the peer reviewers stated that their exclusion would not detract from the findings of the report. The studies recommended for consideration are: Hendel and Spiegel (A*merican Economic Journal: Applied Economics*, January 2014), Balasubramanian and Lieberman (*The Journal of Industrial Economics*, 2011) and Haunschild and Rhee (Ma*nagement Science,* November 2004).

3.5 Data Analyses Conducted

All three peer reviewers found data analyses reasonable and appropriate for the objectives of the study. Dr. Lieberman stated that the report surveyed "a substantial amount of literature" and that it characterizes the literature well. Similarly, Dr. Syverson commented that the report "does an excellent job of sorting through the large research literature to focus on studies that are most germane to its mission."

Reviewers posed a few comments on the elements considered within the studies and across the sector. For example, Dr. Lieberman stated that the studies are not based on the total costs of production; therefore, forecasts will need to consider cost reduction of parts. He recommended further information of the nature of the studies' cost analysis would be helpful to improve the transparency of the approach proposed in the report. Dr. Lieberman also suggested that the report highlight the difficulties of incorporating learning and economies of scale as separate elements, and discuss the slope of the learning curve.

Dr. Balasubramanian requested clarification as to whether all five studies used econometric techniques to causally estimate the effect of learning-by-doing. He recommended that the report "characterize the estimated weighted-average progress ratio as the association between unit costs and cumulative output, rather than as the effect of learning on costs."

Furthermore, the reviewer also noted that it is not clear that all studies used the same method to compute standard error.

Finally, Dr. Syverson stated that the report should clarify the discussion on shipment inventory.

3.6 Appropriateness of the Conclusions

The peer reviewers unanimously support the conclusions reached in the study. Dr. Syverson specifically commented on the study's interpretation that heterogeneity in learning rates may be large within and across organizations and industries, and concurred that it is a critical aspect to highlight. Dr. Lieberman listed several strengths of the report, and stated that it "is likely to be helpful in providing a basis for incorporating forecasts of learning into EPA and other government rulemaking." Dr. Balasubramanian remarked that the conclusion is "well-founded and largely indisputable."

It should be noted that while Dr. Lieberman suggested that, with respect to the estimated progress ratio, a more conservative approach would be to use the smallest learning rate of the sample of five studies (87%), he also agreed that because the five studies used to estimate the mobile source progress ratio are in the same range, "[d]epending on the purpose at hand, one could justify using 84.3% or 87%, in my opinion."

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Balasubramanian, N. and M. B. Lieberman. (2011). Learning-by-doing and market structure. *The Journal of Industrial Economics*. 54(2): 177-198

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Hendel, I. and Y. Spiegel. (2014). Small steps for workers, a giant leap for productivity. *American Economic Journal: Applied Economics. 6*(1): 73–90

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APPENDIX A
CONFLICT OF INTEREST ANALYSIS AND BIAS QUESTIONNAIRE

<u>Conflict of Interest Analysis and Bias Disclosure Form</u>

Instructions:

This disclosure form has been developed in accordance with EPA's Peer Review Handbook, 4th Edition (2015). The questions help identify any conflicts of interest and other concerns regarding each candidate reviewer's ability to independently evaluate the compendium study on industrial learning in the mobile source sector, developed by ICF International. The compendium, entitled "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources" (<u>referred to as "subject topic" on the following page</u>), is intended to be used by EPA to ensure that the learning impacts in EPA's cost estimates are based on a comprehensive survey of the literature and focused on learning effects in the mobile sources sector.

Please answer Yes or No in response to each question to the best of your knowledge and belief. If you answer Yes to any of the questions, please provide a detailed explanation on a separate sheet of paper.

Answering Yes to any of the questions will not necessarily result in disqualification, but a record of any conflicts of interest is necessary to ensure that the peer review is composed of an unbiased group of peer reviewers. RTI International will include the responses as part of the published peer review record.

It is expected that the candidate make a reasonable effort to obtain the answers to each question. For example, if you are unsure whether you or a relevant associated party (e.g., spouse, dependent, significant other) has a relevant connection to the peer review subject, a reasonable effort such as calling or emailing to obtain the necessary information should be made.

By signing the attached form you certify that:

1. You have fully and to the best of your ability completed this disclosure form,
2. You will update your disclosure form promptly by contacting the RTI International peer review facilitator if relevant circumstances change,
3. You are not currently arranging new professional relationships with, or obtaining new financial holdings in, an entity (related to the peer review subject) which is not yet reported, and
4. This signature page, based on information you have provided, and your CV may be made public for review and comment.

U.S. Environmental Protection Agency
Conflict of Interest Inquiry

You have been requested by EPA to serve as a Peer Reviewer for the compendium study "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources" (referred to below as "subject topic"), and your involvement in certain activities could pose a conflict of interest or create the appearance of a loss of impartiality in your review. Although your involvement in these activities is not necessarily grounds for exclusion from the peer review, affiliations or activities that could potentially lead to conflicts of interest are included in the table. Please complete the table and sign the certification below. If you have any questions, contact jrichkus@rti.org at your earliest convenience to discuss any potential conflict of interest issues.

Conflict of Interest Analysis		
	YES	**NO**
a. To the best of your knowledge and belief, is there any connection between the subject topic and any of your and/or your spouse's compensated or uncompensated employment, including government service, during the past 24 months?		
b. To the best of your knowledge and belief, is there any connection between the subject topic and any of your and/or your spouse's research support and project funding, including from any government source, during the past 24 months?		
c. To the best of your knowledge and belief, is there any connection between the subject topic and any consulting by you and/or your spouse, during the past 24 months?		
d. To the best of your knowledge and belief, is there any connection between the subject topic and any expert witness activity by you and/or your spouse, during the past 24 months?		
e. To the best of your knowledge and belief, have you, your spouse, or dependent child, held in the past 24 months, any financial holdings (excluding well-diversified mutual funds and holdings, with a value less than $15,000) with any connection to the subject topic?		
f. Have you made any public statements or taken positions on or closely related to the subject topic under review?		
g. Have you had previous involvement with the development of the document (or review materials) you have been asked to review?		
h. To the best of your knowledge and belief, is there any other information that might reasonably raise a question about an actual or potential personal conflict of interest or bias?		
i. To the best of your knowledge and belief, is there any financial benefit that might be gained by you or your spouse as a result of the outcome of this review?		

CERTIFICATION

I hereby certify that I have read the above statements and, to the best of my knowledge and belief, no conflict of interest exists that may diminish my capacity to provide an impartial, technically sound, objective review of the subject matter or otherwise result in a biased opinion.

____
(Name – please print)

____
(Signature)

____
(Date)

APPENDIX B

PEER REVIEWER RESUMES

Natarajan Balasubramanian
Associate Professor (Strategy)
Whitman School of Management
Syracuse University
721 University Ave, Syracuse, NY 13244. Email: nabalasu@syr.edu

Current Position

Associate Professor, Whitman School of Management, 2013-

Prior Related Employment

Assistant Professor, Whitman School of Management, (2009-2013)

Assistant Professor (Strategy), College of Business Administration, Florida International University, Miami (2007-2009)

Adjunct Lecturer, Stephen M Ross School of Business, University of Michigan, Ann Arbor, Michigan (Mar 2006-Apr 2006)

Teaching and Research Assistant, UCLA Anderson School of Management, Los Angeles, California (2002-2007)

Prior Corporate Employment

Manager, Andersen, Saudi Arabia (2002)

Customer Relationship Manager, Infosys, USA (2001-02)

Senior Consultant, Arthur Andersen, India (1996-2000)

Education

- PhD (Management), UCLA Anderson School of Management (2007)
  (Dissertation Committee Chair: Marvin Lieberman)
- M.A. (Economics), UCLA (2005)
- PGDM (MBA), Indian Institute of Management, Bangalore, India (1996)
- B. Tech (BS) in Chemical Engineering, Indian Institute of Technology, Madras, India (1994)

Published Works

- Starr E., Balasubramanian N. and Sakakibara, M., 2014. Enforcing Covenants Not to Compete: The Life-Cycle Impact on New Firms, in *Academy of Management Proceedings*, 2014:1 13238; doi:10.5465/AMBPP.2014.216
- Lee J. and Balasubramanian N., 2013. Who leads whom? Technological leadership in nanotechnology: Evidence from patent data, in *Restoring America's Global Competitiveness through Innovation*, Eds. Ben Kedia and Subash Jain., Edward Elgar Publishing.
- Ramanathan, S., Balasubramanian, N. and Krishnadas, R, 2013. Is the Macroeconomic Environment during Infancy a Risk Factor for Adolescent Behavioral Problems? *JAMA Psychiatry*, 70(2):218-25.

- Balasubramanian N., 2011. New Plant Venture Performance Differences Among Incumbent, Diversifying, and Entrepreneurial Firms: The Impact of Industry Learning Intensity. *Management Science*. 57(3): 549-565
- Balasubramanian N. and Lieberman M., 2011. Learning by Doing and Market Structure. *Journal of Industrial Economics*. 59(2): 177-198 (Lead Article)
- Balasubramanian N. and Sivadasan J., 2010. What happens when firms patent? New evidence from US Census Data. *Review of Economics and Statistics.* 93(1) 126:146
- Balasubramanian N. and Lieberman M., 2010. Industry Learning Environments and the Heterogeneity of Firm Performance, *Strategic Management Journal*, 31(4), pp. 390-412.
    - Also as Balasubramanian N. and Lieberman M., *Industry Learning Environments and the Heterogeneity of Firm Performance*, In K. Mark Weaver (Ed.), Proceedings of the Sixty-Fifth Annual Meeting of the Academy of Management (CD), ISSN 1543-8643.
- Balasubramanian N. and Sivadasan J., 2009. Capital Resalability, Productivity Dispersion and Market Structure, *Review of Economics and Statistics*, 91(3), pp. 547-557.
- Balasubramanian N. and Lee J., 2008. Firm Age and Innovation, *Industrial and Corporate Change* 17(5), pp. 1019-1047.
    - Also as Balasubramanian N. and Lee J., *Firm Age and Innovation*, In George T. Solomon (Ed.), Proceedings of the Sixty-Sixth Annual Meeting of the Academy of Management (CD), ISSN 1543-8643.
- Chacar A, Balasubramanian N. and Vissa B., *Does it pay to be a Business Group Member?* 2008 Proceedings of the Academy Of International Business-SE (USA)

Works under Revision

- Starr E., Balasubramanian N. and Sakakibara, M. Enforcing Covenants Not to Compete: The Life-Cycle Impact on New Firms (*Management Science, 2nd Round R&R*)
    - Also as Working Paper CES 14-27, *Center for Economic Studies, U.S. Census Bureau*
- Balasubramanian N., Lee, J., and Sivadasan J. Deadlines, Work Flows, Task Sorting, and Work Quality (*Management Science, 2nd Round R&R*)
- Garcia, R., Balasubramanian N. and Lieberman M. Measuring Value Creation and Appropriation in Firms: Application of the VCA Model (*Strategic Management Journal, 1st Round R&R*)
- Lieberman M., Balasubramanian N. and Garcia, R. Toward a Dynamic Notion of Value Creation and Appropriation in Firms: The Concept and Measurement of Economic Gain (*Strategic Management Journal, 2nd Round R&R*)

Working Papers

- Balasubramanian, N., Chang J.W., Sakakibara, M., Sivadasan J. and Starr E. Locked in? Noncompete Enforceability and the Mobility and Earnings of High Tech and High Earnings Workers
- Sakakibara, M. and Balasubramanian N. Human Capital of Spinoffs. Working Paper CES 15-06, *Center for Economic Studies, U.S. Census Bureau*

- Sakakibara, M. and Balasubramanian N. Spinout Formation: Do Opportunities and Constraints Benefit High Human Capital Founders? Working Paper CES 15-07, *Center for Economic Studies, U.S. Census Bureau*
- Sakakibara, M. and Balasubramanian N. Incidence and Performance of Spinoffs: A Cross-Industry Analysis.
- Balasubramanian N., and Deb, P. Learning by Doing and Capital Structure
- Balasubramanian N., Dharwadkar, R., and Sivadasan J. Firm Growth and Governance: Running to Stand Still?
- Dharwadkar, R., Balasubramanian N., and Suh, S. Managerial Insulation and Research and Development Investments: An Empirical Examination.

Competitive Awards and Grants

- Kauffman Junior Faculty Fellow in Entrepreneurship Research, 2012
- Whitman Research Fellow, Whitman School of Management, 2014-2015
- Guttag Junior Faculty Award, Whitman School of Management, 2012
- Finalist, *Outstanding Dissertation Award Competition*, BPS Division, Academy of Management, 2008
- Entrepreneurship Research Grant, Winter 2008 (Joint with Jeongsik Lee, Georgia Inst. of Tech.)
- UCLA Dissertation Year Fellowship (2006-2007)
- California Census Research Data Center Dissertation Fellowship (2005-2007)
- Gladys Byram Fellowship (2002-2006)

External Service Activities

- Member, Editorial Board, Journal of Management (2014-)
- Member, Research Committee, BPS Division, Academy of Management (2015-)
- Ad hoc reviewer: National Science Foundation, Kauffman Foundation, Management Science, Strategic Management Journal, Organization Science, Journal of Management Studies, Strategic Entrepreneurship Journal, Journal of Industrial Economics, Journal of Labor Economics, Journal of Economics & Management Strategy, BE Journal of Economic Analysis & Policy, Research Policy, Journal of Business Venturing, European Financial Management

Internal Service Assignments

- Department Representative, Doctoral Board, Whitman School of Management (2014-)
- Member, Promotion & Tenure Committee, Whitman School of Management (2014-2015)
- Department Representative, Undergraduate Board, Whitman School of Management (2009-2014)
- Co-director, Department Speaker Series (2011-13)
- Conducted several "How to Prepare for a Case" Sessions in the 1st Year MBA Orientations
- Judge for Whitman Annual Case Competitions
- Member, Journal List Committee, College of Business, Florida International University, (2007-09)

Presentations

- Florida International University, January 2016 (Invited)
- Strategic Science Mini Conference, Philadelphia, November 2015 (Invited)
- Whitman School of Management, February and April 2015
- Kauffman Emerging Scholars Conference, Kansas City, October 2014 (Invited)
- Annual Meeting of the Academy of Management, Philadelphia, August 2014 (Peer-reviewed)
- Goizueta School of Business, Emory University, November 2012 (Invited)
- Annual Meeting of the Academy of Management, Boston, August 2012 (Peer-reviewed)
- Krannert School of Management, Purdue University, October 2011 (Invited)
- Stern School of Business, NYU, August 2011 (Invited)
- Annual Meeting of the Academy of Management, Chicago, August 2009 (Peer-reviewed)
- Annual Meeting of the Academy of Management, Anaheim, August 2008 (Peer-reviewed)
- Annual Meeting of the American Economic Association, 2008 (Peer-reviewed)
- Annual Meeting of the Academy of Management, Atlanta, August 2006 (Peer-reviewed)
- Atlanta Competitive Advantage Conference, June 2006 (Peer-reviewed)
- The Evolution of Ideas in Innovation and Entrepreneurship: A Conference to Honor Michael Gort's Contributions, University of Washington, St Louis, June 2006 (Invited)
- Annual Meeting of the Academy of Management, Honolulu, August 2005 (Peer-reviewed)
- Annual Meeting of the Western Economic Association, San Francisco, July 2005 (Peer-reviewed)
- Business and its Social Environment (BASE) Conference, Kellogg School of Business, June 2005 (Peer-reviewed)
- Innovation Workshop, Anderson School of Management, UCLA, May 2005
- Consortium for Competition and Co-operation (CCC), UC Berkeley, April 2005

Teaching Experience

- Whitman School of Management, Syracuse University.

Courses: SHR 247; SHR 447; MBC 618; MBC 619; MBC 645 (Strategic Management for Undergraduates and Graduates)

- College of Business Administration, Florida International University, Miami (2007-2009)

  Courses: Strategic Management (for Undergraduates and Graduates)

- Stephen M Ross School of Business, University of Michigan, Ann Arbor, Winter 2006.

  Course: Competitive Tactics and Competition Policy, MBA Elective.

- Teaching Assistant, University of California, Los Angeles, 2002-2006.

  Courses: Business Strategy and Negotiations Analysis

Teaching Awards

- Best Professor, Downtown MBA Program, Florida International University (April 2008)

Professional Memberships

- Member, Academy of Management
- Member, American Economic Association

MARVIN B. LIEBERMAN

Office Address:
UCLA Anderson School of Management
Gold Hall, Room B-415
Los Angeles, CA 90095-1481
(310) 206-7665
E-mail: marvin.lieberman@anderson.ucla.edu

Home Address:
180 Acacia Lane
Newbury Park, CA 91320

Education

Ph.D.	Harvard University	Business Economics	1982
A.B.	Harvard University	Economics	1976

Dissertation

Title: The Learning Curve, Pricing, and Market Structure in the Chemical Processing Industries

Committee: Richard E. Caves, Michael E. Porter, A. Michael Spence

Academic Positions

2001 - present: Professor, UCLA Anderson School of Management

1990 - 2001: Associate Professor, Anderson Graduate School of Management, UCLA

1989 - 1990: National Fellow, Hoover Institution

1982 - 1989: Assistant Professor of Business Policy, Graduate School of Business, Stanford University

1979 - 1981: Teaching Fellow (Introductory Economics), Harvard University

Academic Honors

Strategic Management Society Fellow
TMS Distinguished Speaker, Fall 2009 INFORMS Conference
1996 Best Paper Prize, *Strategic Management Journal*
Hoover National Fellowship, 1989-90
Shigeo Shingo Prize for Manufacturing Excellence, 1989
Harvard Business School Division of Research Thesis Fellowship, 1981
Browder Thompson Best Paper Award (IEEE), 1979
National Science Foundation Fellowship, 1976-80

Journal Articles

"Entry, Exit and the Potential for Resource Redeployment," (with Gwendolyn Lee and Tim Folta). Forthcoming, *Strategic Management Journal*.

Best paper award finalist, BPS Division, 2010 Academy of Management Meeting.

"Production Frontier Methodologies and Efficiency as a Performance Measure in Strategic Management Research," (with C.M. Chen and Magali Delmas). *Strategic Management Journal*, Vol. 36, January 2015, pp. 19-36.

"Conundra and Progress: Research on Entry Order and Performance," (with David Montgomery). *Long Range Planning*, Special Issue on Entry Timing Strategies, Vol. 46, August 2013, pp. 313-324.

"Learning by Doing and Market Structure," (with Natarajan Balasubramanian). *Journal of Industrial Economics*, Vol. 59, No. 2, June 2011, pp. 177-198.

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"The Learning Curve, Technology Barriers to Entry, and Competitive Survival in the Chemical Processing Industries." *Strategic Management Journal*, Vol. 10, No. 5, September-October 1989.

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"First-Mover Advantages," (with David Montgomery). *Strategic Management Journal*, Vol. 9, Summer 1988.

Recipient of 1996 *SMJ* Best Paper Prize (awarded for articles more than five years old with significant impact on the field of strategic management).

Reprinted in *Readings in Marketing Strategy*, V. J. Cook, J. Larreche and E. C. Strong, eds., Scientific Press, Redwood City, 1989.

Reprinted in *Strategic Management*, (volume of the International Library of Critical Writings on Business and Management), J. Birkenshaw, ed., Edward Elgar, London, 2003.

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"Post-Entry Investment and Market Structure in the Chemical Processing Industries," *Rand Journal of Economics*, Vol. 18, No. 4, Winter 1987.

"Market Growth, Economies of Scale, and Plant Size in the Chemical Processing Industries," *Journal of Industrial Economics*, Vol. 36, No. 2, December 1987.

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"Strategies for Capacity Expansion," *Sloan Management Review*, Vol. 28, No. 4, Summer 1987.

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Reprinted in *The Empirical Renaissance in Industrial Economics*, T. Bresnahan and R. Schmalensee, eds., Basil Blackwell, London, 1987.

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Browder Thompson prize for best research paper by an author under 30 published in an IEEE journal during 1978.

Conference Proceedings (Published)

"An Extension of the VCA Model To Estimate Stakeholder Value Appropriation" (with Roberto Garcia), *Best Papers Proceedings, Academy of Management*, 2012.

"Relatedness and Market Exit," (with Gwendolyn Lee and Tim Folta), *Best Papers Proceedings, Academy of Management*, 2010. BPS Division Best Paper Award finalist.

"Acquisition vs. Internal Development as Entry Modes for New Business Development: The Dynamics of Firm-Market Relevance," (with Gwendolyn Lee), *Best Papers Proceedings, Academy of Management*, 2007.

"Industry Learning Environments and the Heterogeneity of Firm Performance," (with Natarajan Balasubramanian), *Best Papers Proceedings, Academy of Management*, 2006.

"Why Do Firms Behave Similarly? A Study on New Product Introduction in the Japanese Soft-drink Industry," (with Shigeru Asaba), *Best Papers Proceedings, Academy of Management*, 1999.

"Determinants of Vertical Integration: An Empirical Test," *Best Papers Proceedings, Academy of Management*, 1991.

Book Chapters

"Business Model Innovation and Replication: Implications for the Measurement of Productivity," (with Natarajan Balasubramanian, Joan Enric Ricart and Roberto Garcia Castro). Forthcoming as Chapter 10 of *Productivity and Business Strategy*, Oxford University Press.

"First Mover/ Pioneer Strategies," (with David Montgomery), in Venkatesh Shankar and Gregory S. Carpenter, eds., *Handbook of Marketing Strategy*, (Edward Elgar, 2012).

"Business Imitation," (with Shigeru Asaba), in Charles Wankel, ed., *Handbook of 21st Century Management* (Sage, 2007).

"Organizing for Technological Innovation in the U.S. Pharmaceutical Industry," (with Aya Chacar), in Joel Baum and Olav Sorenson, eds., *Geography and Strategy* (Advances in Strategic Management, Volume 20, Elsevier, 2003).

"Dow Chemical and the Magnesium Industry," in D. I. Rosenbaum, ed., *Market Dominance: How Firms Gain, Hold or Lose It and the Impact on Economic Performance*, Praeger, Westport, CT, 1998, pp. 69-87.

"Distribution of Returns Among Stakeholders: Method and Application to US and Japanese Auto Companies," (with Aya Chacar), in H. Thomas and D. O'Neal, eds., *Strategic Discovery: Competing in New Arenas*, Wiley, 1997, pp. 299-313.

"Strategy of Market Entry: Pioneer or Follow?" (with David Montgomery). In *Handbook of Business Strategy*, H. E. Glass, ed., Warren, Gorham & Lamont, 1991.

"Inventory Reduction and Productivity Growth: A Study of Japanese Automobile Producers." In *Manufacturing Strategy*, J. E. Ettlie, M. C. Burstein and A. Feigenbaum, eds., Kluwer Academic Publishers, 1990.

"Learning, Productivity, and US-Japan Industrial Competitiveness." In *Managing International Manufacturing*, K. Ferdows, ed., North Holland, 1989.

"Estimating the Benefits to Society from Integrated Circuit Innovations: the Case of MOS Dynamic RAM's," in R. Wilson et al., *Innovation, Competition and Government Policy in the Semiconductor Industry*, Lexington Books, 1981, pp. 122-31.

Other Publications

"First Mover Advantages," in *Palgrave Encyclopedia of Strategic Management, 2013*.

"Just-in-Time," in *Palgrave Encyclopedia of Strategic Management, 2013*.

"Cost," in *Palgrave Encyclopedia of Strategic Management, 2013*.

"Sunk Cost," in *Palgrave Encyclopedia of Strategic Management, 2013*.

"Cost Leadership," in *Palgrave Encyclopedia of Strategic Management, 2014*.

"The Revitalization of US Manufacturing," Institute for International Economic Studies, Tokyo, Japan, Seminar Series 9706, June 1997.

Papers Under Review and Work in Progress

Market Entry

"Who Imitates Whom? A Study on New Product Introductions in the Japanese Soft-drink Industry," (with Shigeu Asaba), January 2011. (Presented at USC, UCLA, Academy of Management annual meeting (2012), Industry Studies Association Conference (2013).)

"Did First-Mover Advantage Survive the Dot-Com Crash?" December 2007. (Presented at CMU, Emory, Maryland, NYU, Wharton, UC Berkeley, UCLA, University of Illinois, and the Stanford and Utah Strategy Conferences.)

Economic Value Creation

"Measuring Value Creation and Appropriation in Firms: The VCA Model" (with Natarajan Balasubramanian and Roberto Garcia). Under 3rd round review, *Strategic Management Journal*.

"Toward a Dynamic Notion of Value Creation and Appropriation in Firms: The Concept and Measurement of Economic Gain," (with Natarajan Balasubramanian and Roberto Garcia). Under 2nd round review, *Strategic Management Journal*.

Cases and Teaching Notes

Lectures on "Creation and Distribution of Economic Value"
The Magnesium Industry in 1964 (A), S-BP-231A
The Magnesium Industry 1964-1974 (B), S-BP-231B
The Magnesium Industry 1974-1982 (C), S-BP-231C
Magnesium Industry Teaching Note
Learning Curve Computer Exercise
Teaching Note on the Learning Curve Computer Exercise
Note on Production Economics: Cost Structures and Process Types

Courses Taught

Business Strategy
Industry Structure and Competitive Strategy
Market Entry Strategy
Entrepreneurial Perspectives on Biotechnology
Strategies for Internet Business
Production/Operations Management
Introductory Economics

Invited Presentations

Carnegie-Mellon University
Columbia University
Dartmouth (Tuck)
Duke University
Emory University
Florida International University
Harvard University
INSEAD
Institute for International Economic Studies
Kobe University
London Business School
Massachusetts Institute of Technology
New York University
Northwestern University
Peking University
Southern Methodist University
University of British Columbia
University of California, Berkeley

University of California, Irvine
University of California, San Diego
University of Chicago
University of Illinois, Champaign-Urbana
University of Maryland
University of Michigan
University of Minnesota
University of Pennsylvania (Wharton)
University of Pittsburgh
University of Rochester
University of Southern California
University of Texas at Austin
University of Toronto
University of Washington
University of Wisconsin, Madison
U.S. Department of Justice
U.S. Federal Trade Commission
Washington University at St. Louis

Professional Societies

Academy of Management
American Economic Association
Strategic Management Society (Fellow)
Industry Studies Association

Editorial

Strategic Management Journal (Editorial Board)
Production and Operations Management (Senior Editor)

Revised: February 2016

CHAD SYVERSON

Curriculum Vitae
(January 2016)

University of Chicago Booth School of Business
5807 S. Woodlawn Ave.
Chicago, IL 60637
Phone: (773) 702-7815
chad.syverson@chicagobooth.edu
syverson@uchicago.edu

ACADEMIC POSITIONS

J. Baum Harris Professor of Economics; University of Chicago Booth School of Business, 2013-Present
Professor of Economics; University of Chicago Booth School of Business, 2008-2013
(*Charles M. Harper Faculty Fellow*, 2012-2013)
Associate Professor (with tenure); Department of Economics, University of Chicago, 2007-2008
Associate Professor; Department of Economics, University of Chicago, 2006-2007
Assistant Professor; Department of Economics, University of Chicago, 2001-2006

OTHER PROFESSIONAL APPOINTMENTS

Editor; *RAND Journal of Economics*, 2013-Present
Editor; *Journal of Industrial Economics*, 2013-2014
Associate Editor; *Management Science*, 2011-Present
Associate Editor; *Journal of Economic Perspectives*, 2012-2015
Associate Editor; *Journal of Economics & Management Strategy*, 2010-2014
Associate Editor; *RAND Journal of Economics*, 2007-2013
Associate Editor; *Journal of Industrial Economics*, 2005-2013
Editorial Board Member; *B.E. Journals in Economic Analysis and Policy*, 2005-2013
Research Associate; National Bureau of Economic Research (Productivity, Industrial Organization, and Environmental and Energy Economics Programs), 2003-Present
Visiting Scholar; Federal Reserve Bank of Minneapolis, 2003, 2004, 2005

EDUCATION

Ph.D. Economics, University of Maryland, 2001
M.A. Economics, University of Maryland, 1998
B.S. Mechanical Engineering, University of North Dakota, 1996
B.A. Economics, University of North Dakota, 1996

PUBLICATIONS

"Healthcare Exceptionalism? Performance and Allocation in the U.S. Healthcare Sector" *American Economic Review* (with Amitabh Chandra, Amy Finkelstein, and Adam Sacarny), forthcoming.

"Productivity Dispersion in Medicine and Manufacturing" (with Amitabh Chandra, Amy Finkelstein, and Adam Sacarny) *American Economic Review Papers and Proceedings*, forthcoming.

Microeconomics, 2nd Ed. (with Austan Goolsbee and Steve Levitt), Worth, 2016.

"The Slow Growth of New Plants: Learning about Demand." (with Lucia Foster and John Haltiwanger.) *Economica*, 83(329), (January 2016), 91-129.

"Geographic Variation in Rosiglitazone use Surrounding FDA Warnings in the Department of Veterans Affairs" (with Vishal Ahuja, Min-Woong Sohn, John R. Birge, Elly Budiman-Mak, Nicholas Emanuele, Jennifer M. Cooper, and Elbert S. Huang), *Journal of Managed Care & Specialty Pharmacy*, 21(12), (December 2015), 1214-34.

"The Ongoing Evolution of US Retail: A Format Tug-of-War" (with Ali Hortaçsu), *Journal of Economic Perspectives*, 29(4), (Fall 2015), 89-112.

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"Acquisitions, Productivity, and Profitability: Evidence from the Japanese Cotton Spinning Industry" (with Serguey Braguinsky, Atsushi Ohyama, and Tetsuji Okazaki), *American Economic Review*, 105(7), (July 2015), 2086-2119.

"Vertical Integration and Input Flows" (with Enghin Atalay and Ali Hortaçsu), *American Economic Review*, 104(4), (April 2014), 1120-48.

Review of Vaclav Smil's "Made in the USA: The Rise and Retreat of American Manufacturing." *Journal of Economic Literature*, 52(3), (September 2014), 872-3.

"The Importance of Measuring Dispersion in Firm-Level Outcomes." in *IZA World of Labor*, May 2014.

"Toward an Understanding of Learning by Doing: Evidence from an Automobile Plant" (with Steve Levitt and John A. List), *Journal of Political Economy*, 121(4), (August 2013), 643-681.

"Indirect Costs of Financial Distress in Durable Goods Industries: The Case of Auto Manufacturers" (with Ali Hortaçsu, Gregor Matvos, and Sriram Venkataraman), *Review of Financial Studies*, 26(5), (May 2013), 1248-1290.

Microeconomics. (with Austan Goolsbee and Steve Levitt), Worth, 2013.

"Will History Repeat Itself? Comments on 'Is the Information Technology Revolution Over?'" *International Productivity Monitor*, 25, (Spring 2013), 37-40.

"Online vs. Offline Competition" (with Ethan Lieber), in *Oxford Handbook of the Digital Economy*, Martin Peitz and Joel Waldfogel (eds.), 2012, 189-223.

"What Determines Productivity?" *Journal of Economic Literature*, 49(2), (June 2011), 326-65.

“Is an Automaker’s Road to Bankruptcy Paved with Customers’ Beliefs?” (with Ali Hortaçsu, Gregor Matvos, Chaehee Shin, and Sriram Venkataraman), *American Economic Review Papers and Proceedings*, 101(3), (May 2011), 93-7.

“Network Structure of Production.” (with Enghin Atalay, Ali Hortaçsu and Jimmy Roberts) *Proceedings of the National Academy of Sciences*, 108(13), (March 29, 2011), 5199-5202.

“Technological Change and the Growing Inequality in Managerial Compensation.” (with Hanno Lustig and Stijn Van Nieuwerburgh) *Journal of Financial Economics*, 99(3), (March 2011), 601-27.

“E-commerce and the Market Structure of Retail Industries.” (with Maris Goldmanis, Ali Hortaçsu, and Onsel Emre.) *Economic Journal*, 120(545), (June 2010), 651-82.

“How Do Incumbents Respond to the Threat of Entry? Evidence from the Major Airlines.” (with Austan Goolsbee.) *Quarterly Journal of Economics*, 123(4), (November 2008), 1611-33.

“Market Distortions when Agents are Better Informed: The Value of Information in Real Estate Transactions.” (with Steve Levitt.) *Review of Economics and Statistics* 90(4), (November 2008), 599-611.

“Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?” (with Lucia Foster and John Haltiwanger.) *American Economic Review* 98(1), (March 2008), 394-425.

“Markets: Ready-Mixed Concrete.” *Journal of Economic Perspectives* 22(1), (Winter 2008), 217-33.

“Antitrust Implications of Home Seller Outcomes when using Flat-Fee Real Estate Agents.” (with Steve Levitt.) *Brookings-Wharton Papers on Urban Affairs, 2008*, 47-93.

“Prices, Spatial Competition, and Heterogeneous Producers: An Empirical Test.” *Journal of Industrial Economics* 55(2), (June 2007), 197-222.

“Cementing Relationships: Vertical Integration, Foreclosure, Productivity, and Prices.” (with Ali Hortaçsu.) *Journal of Political Economy* 115(2), (April 2007), 250-301.

“Market Structure and Productivity: A Concrete Example.” *Journal of Political Economy* 112(6), (Dec. 2004), 1181-1222.

“Product Differentiation, Search Costs, and the Welfare Effects of Entry: A Case Study of S&P 500 Index Funds.” (with Ali Hortaçsu) *Quarterly Journal of Economics* 119(4), (May 2004), 403-456.

“Product Substitutability and Productivity Dispersion.” *Review of Economics and Statistics* 86(2), (May 2004), 534-550.

“Leak Testing of a Raised Face Weld Neck Flange.” (with George Bibel, Dion Weinberger, and Steven Dockter), *Welding Research Council Bulletin*, (January 2002).

SUBMITTED PAPERS/WORKING PAPERS

"Competition and Regulation of Advertising: Evidence from Privatized Social Security in Mexico." (with Justine Hastings and Ali Hortaçsu)

"The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing" (with Michael Greenstone and John A. List)

"Once and Done: Leveraging Behavioral Economics to Increase Charitable Contributions" (with Amee Kamdar, Steve Levitt, and John A. List)

RESEARCH PROJECTS AND AWARDS

PI, "Empirical Studies of Production in Plants and Firms." NSF Award SES-0820307, 2008-2010.

PI, "Empirical Research on Vertical Integration and Productivity." NSF Award SES-0519062, 2005-2007.

"Patterns of Firm Expansion." (with Ali Hortaçsu) Chicago Census Research Data Center, Project CH-00573, 2007-2012.

"E-commerce and the Market Structure of Retail Industries." (with Ali Hortaçsu). NET Institute, 2005.

Co-PI (with Ali Hortaçsu), "Entry, Competition, and Welfare in the Mutual Fund Industry." NSF Award SES-0242031. 2003-2005.

"How Do Incumbents Respond to the Threat of Entry on Their Networks: Evidence from the Major Airlines." (with Austan Goolsbee). NET Institute, 2004.

"Technology Dispersion and Persistence within Industries." Olin Foundation Grant, University of Chicago, 2005.

"Studies in Productivity." Olin Foundation Grant, University of Chicago, 2004.

"Market Structure and Competition in the Mutual Fund Industry." (with Ali Hortaçsu.) Olin Foundation Grant, University of Chicago, 2002.

"Productivity Heterogeneity and Market Segmentation." Chicago Census Research Data Center, Project CH-00276, 2003-2005.

"Vertical Integration." (with Ali Hortaçsu) Chicago Census Research Data Center, Project CH-00277, 2003-2005.

"Economics of Production." Social Sciences Divisional Research Grant, University of Chicago. 2002-2003.

"Using Market Segmentation to Identify Plant-Specific Instruments." Center for Economic Studies, U.S. Census Bureau, Project WO99-21, 1999-2001.

OTHER RESEARCH

Output Market Segmentation, Heterogeneity, and Productivity
Ph.D. Dissertation, University of Maryland, 2001. Profs. John Haltiwanger and John Shea, Co-Chairs

"Production Function Estimation with Plant-Level Data: Productivity Proxies or Instrumental Variables?" 2000.

"Healthcare Exceptionalism? Productivity and Allocation in the U.S. Healthcare Sector" NBER Working Paper 19200 (with Amitabh Chandra, Amy Finkelstein, and Adam Sacarny)

INVITED PRESENTATIONS

Aarhus (keynote), American Enterprise Institute, Arizona, ASSA Annual Meeting (multiple), Banco de Portugal, Bank of Canada, BEA (2), BLS, Boston University, Brookings Institution, CAED 2008, 2010 (keynote) and 2012, CEA 2012 Meetings (keynote), Carnegie Mellon, CEPR IO Meetings 2009 (keynote), Clemson, Colorado, Columbia GSB (3), Competition Bureau of Canada, Dartmouth (Tuck), Department of Justice Antitrust Division, Drexel (2), Duke (3), EARIE (keynote), ECB (keynote), ESEM, FRB Chicago, FRB Cleveland, FRB Kansas City, FRB Minneapolis (3), FRB Philadelphia, Fed Board of Governors (2), FTC, Georgetown, Harvard (Econ. [4] and HBS [2]), Illinois, Illinois-Chicago, Indiana, Iowa, Iowa State (2), Kentucky, LSE (3), Mannheim, Michigan (Econ. [2] and Ross), Michigan State, Minnesota (2), MIT (Econ. [3] and Sloan [3]), National Bank of Belgium (keynote), NBER IO and Productivity meetings (multiple), NBER Summer Institute (multiple), NET Institute Conference 2005-2006, North Dakota (2), Northwestern (Kellogg GSB [2]), Notre Dame, NYU (Econ. and Stern [2]), OECD (2), Penn (Wharton), Penn State, Pittsburgh, Princeton (2), Purdue (2), Rice, Rochester, SED 2004 and 2010, SITE 2003 and 2007-2008, Stanford (Econ and GSB [2]), Texas A&M, Toronto (Rotman [2]), UBC (Sauder [2]), UC-Berkeley (Haas [4]), UC-Irvine, UCLA (3), UCSD (2), UNSW, Utah Winter Business Economics Conference (2), University of Washington, Washington Univ.-St. Louis (Olin), Wisconsin, Yale (3), World Bank, ZEW ICT Workshop 2012 (keynote).

PROFESSIONAL SERVICE

National Academy of Sciences Panel on Reengineering the Census Bureau's Annual Economic Surveys, 2015-.
National Science Foundation Site Visit Review Panel, 2015.
National Academy of Engineering Making Value for America Committee, 2013-2015
National Academy of Engineering Committee on Manufacturing, Design, and Innovation, 2012
Graduate Business Council Faculty-Student Committee, Booth School of Business, 2011-
Census Scientific Advisory Committee (AEA representative), 2009-2012
Chicago Census Research Data Center Advisory Board, 2002-Pres (Chair 2008-).
University Benefits Committee, Univ. of Chicago, 2005-08
Graduate Economics Computer Lab Faculty Advisor, Univ. of Chicago Dept of Econ., 2002-08
Social Sciences Divisional Research Grant Evaluation Committee, Univ. of Chicago, 2003-04.
Faculty Advisory Committee to Social Science Computing, Univ. of Chicago, 2004-08
Committee to Review the Economics Department Chair, Univ. of Maryland, 1999
Co-Chair, Economics Graduate Student Association, Univ. of Maryland, 1997-98
Chapter President, Omicron Delta Epsilon (Economics Honorary), 1995-96

President, Univ. of North Dakota Engineers' Student Council, 1993-94

OTHER PROFESSIONAL EXPERIENCE

Research Assistant; Assistant to Prof. John Haltiwanger; University of Maryland, U.S. Census Bureau, and NBER, 1998-2000

Mechanical Engineer Co-op; Loral Defense Systems, Eagan, MN, and Unisys Corporation, Roseville, MN, 1993-95

Assistant Football Coach, Red River High School; Grand Forks, ND, 1991-93

PROFESSIONAL AFFILIATIONS

Member, American Economic Association

SECURITY CLEARANCE

Special Sworn Status, U.S. Census Bureau

PUBLIC SERVICE

Elected Member of Local School Council, Keller Regional Gifted Center, Chicago Public Schools, 2012-Present; Council Chair, 2014-Present

HONORS AND AWARDS

Distinguished Visiting Scholar, Drexel University School of Economics, 2015
Young Alumni Achievement Award, University of North Dakota Alumni Association, 2013
Charles M. Harper Faculty Fellow, Booth School of Business 2012-13
Excellence in Refereeing Award, *American Economic Review*, 2011-14
Brookings Dissertation Fellowship, 2000-01
University of Maryland Graduate Fellowship, 1996-98
North Dakota Society of Professional Engineers Outstanding Student Award, 1993-96
Graduated Summa Cum Laude, University of North Dakota
Alexis Diakoff Mechanical Engineering Scholarship, University of North Dakota
Bohlman Economics Scholarship, University of North Dakota
Presidential Honor Roll, University of North Dakota, 1991-96
Commencement Grand Marshal, University of North Dakota, 1993
One of 141 National Presidential Scholars named by the White House Commission on Presidential Scholars, and White House guest of President George H. W. Bush, 1991

APPENDIX C
PEER REVIEW PANEL CHARGE

SUBJECT: Charge questions for Peer Review of “Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources”

Thank you for agreeing to review the enclosed report, “Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources.”

EPA undertook this study to improve our cost estimates for our mobile source rulemakings and, specifically, to provide clarity about the effects of industrial learning. We are submitting this document to you for a peer review of the methodology, and the validity and assumptions that go into it.

EPA has provided direction and charge questions for this review and these are included below. A teleconference call will also be arranged so that EPA can respond to questions from individual reviewers on the material that was provided for review. The completed review reports are to be furnished to RTI by April 15, 2016.

Elements to be addressed in the Charge to the Reviewers of the Report on “Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources”

The study is intended to be a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically. It consists of a literature review of studies of learning in mobile source industries, most notably the automotive industry (both original equipment manufacturers and tier 1 suppliers); identifies and summarizes empirical estimates of learning from those studies; develops a methodology to estimate the impacts of learning in the mobile source sectors using the quantitative estimates obtained from the literature review; and develops a best estimate for learning in the mobile source sector.

We request that your review primarily focus on: (1) clarity of the presentation, (2) the overall approach and methodology, (3) appropriateness of the studies included and other inputs, (4) the data analyses conducted, and (5) appropriateness of the conclusions. For this review, no independent data analysis is required, nor is it required that you duplicate the results. In your comments, you should distinguish between recommendations for clearly defined improvements that can be readily made based on data reasonably available to EPA, versus improvements that are more exploratory or dependent on data not available to EPA. The comments should be sufficiently detailed to allow a thorough understanding by EPA or other parties familiar with the work.

Your comments should be provided as an enclosure to a cover letter that clearly states your name, the name and address of your organization, what material was reviewed, a summary of your expertise and qualifications, and a statement that you have no real or perceived conflicts of interest. Please also enclose an email with your comments in MS Word, or a format that can be imported into MS Word. The comments should be sent in care of Jennifer Richkus to the Email: jrichkus@rti.org.

EPA will make the report and your comments available to the public, and we may submit the report and your comments to public dockets that support future rulemakings and studies. We would appreciate you not providing the peer review materials or your comments to anyone else until EPA makes them public. We would also like to receive the results of this review in the shortest time frame possible, preferably within six weeks of your receipt of this request. If you have any questions about what is required in order to complete this review, or if you find you need additional background material, please contact RTI contact by phone (202-974-7831) or e-mail [jrichkus@rti.org]. If you have any questions about the EPA peer review process itself, please direct them to Ms. Ruth Schenk of EPA by phone (734-214-4017) or e-mail [schenk.ruth@epa.gov]

We estimated 40 hours of review time for this peer review. In your cover letter please indicate the number of hours spent on the review; spending fewer or more hours than our estimate will not affect the fee paid for this work, but will help us improve our future budget estimates.

APPENDIX D

PEER REVIEWER QUESTIONS AND ANSWERS ON THE CHARGE

Q. Please provide formal definitions for mobile sources and the mobile source industry.

A. "Mobile sources" include cars and light trucks, heavy trucks and buses, nonroad engines, equipment, and vehicles. More specifically:

- On-road vehicles and engines
  - Cars & Light Trucks
  - Heavy Trucks, Buses & Engines
  - Motorcycles
- Nonroad engines, equipment and vehicles
  - Aircraft
  - Diesel boats and ships
  - Gasoline boats & personal watercraft
  - Nonroad diesel equipment (including excavators and other construction equipment, farm tractors and other agricultural equipment, heavy forklifts, airport ground service equipment, and utility equipment such as generators, pumps, and compressors)
  - Nonroad gasoline equipment (forklifts, generators & compressors)
  - Small gasoline equipment (lawn & garden)
  - Locomotives
  - Snowmobiles, dirt bikes & ATVs

For purposes of the report, EPA defined "mobile source industry" as original equipment auto makers, parts suppliers to those auto makers, loose engine manufacturers, large truck manufacturers, and nonroad equipment manufacturers.

Q. Is the intended task to review the report in the context of its applicability to rulemaking by the EPA?

A. The peer review is intended to review the reasonableness and the comprehensiveness provided by the report, however EPA has asked that peer reviewers look critically at Section 3.4 and comment on whether the recommendations are reasonable given the information provided in the report.

APPENDIX E
PEER REVIEWER REPORTS

April 14, 2016

To,

Jennifer Richkus
Research Environmental Scientist
RTI International

Sub: Review of "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources"

Dear Jennifer:

Please find attached my review of the above-mentioned document. I provide the other required details below.

Materials Reviewed: The review was based on the following materials received via email on March 2, 2016: (i) "Cost Reduction through Learning In Manufacturing Industries and In the Manufacture of Mobile Sources" (ii) Charge Letter. Please refer to the section "Scope of the Review" in my review report for further details.

Summary of Related Expertise and Qualifications: I have a PhD in Management from the Anderson School at the University of California, Los Angeles. My dissertation was on the topic of learning-by-doing, and examined learning-by-doing and its competitive implications in the manufacturing sector. Based on this work, I have published three peer-reviewed articles in the following journals: Strategic Management Journal, Management Science and Journal of Industrial Economics. I have also reviewed manuscripts on this topic for leading journals in the field of management.

Statement Regarding Conflict of Interest: I do not have any real or perceived conflict of interest with respect to the document I reviewed. I was not involved in writing that document nor have I made any public statements about it.

Estimated Hours of Work: ~30 hours

Disclaimer: The opinions, comments and statements made in this review are my own and do not reflect my employer's views.

Sincerely,

Natarajan Balasubramanian, PhD
Associate Professor of Management
Whitman School of Management, Syracuse University
721 University Ave Rm 522
Syracuse, NY, 13244

Review of "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources"

Natarajan Balasubramanian, Ph.D.

April 14, 2016

SCOPE OF THE REVIEW

This review was completed in response to a review request by RTI International made via email on Feb 9, 2016. The materials for review, a report titled "Cost Reduction through Learning In Manufacturing Industries and In the Manufacture of Mobile Sources" ('the Report') by the United States Environmental Protection Agency, numbered EPA-420-R-16-XXX and the Charge Letter were received on March 2, 2016 via email. The aforementioned report contains within it, a study ('the ICF Report'), dated Sep 15, 2015, prepared by ICF International.

The scope of this review was based on the Charge Letter and additional responses to questions asked by reviewers via email and during a conference call on March 23, 2016 with personnel from RTI International and the United States Environmental Protection Agency ('EPA'). In line with these instructions, this review focuses on the following aspects, specifically with respect to the stated objectives of the Report:

1) Reasonableness and comprehensiveness
2) Clarity of the presentation including the organization
3) Suitability of the overall approach and methodology, and the data analyses conducted
4) Appropriateness of the studies included and other inputs, and the
5) Appropriateness of the conclusions and in particular, the recommendations made in Section 3.4 of the ICF Report.

No independent data analysis was conducted. Further, no attempt was made to duplicate the results stated in the Report. The review was based only on the material provided in the Report. Unless stated otherwise, no external material including any original books and articles summarized in the Report was used during the review process. Hence, this review cannot comment on the accuracy of those original books and articles. In accordance with the instructions, the Report was not reviewed in the context of its applicability to rulemaking by the EPA.

STATED OBJECTIVES OF THE REPORT

The Report appears to have four stated objectives.

Objective 1: To be "a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically" (Charge Letter and Section 2 of the ICF Report).

Objective 2: "[T]he goal of this work assignment is to develop a single compendium study on industrial learning in the mobile source sector that can be relied on as the basis for *this effect* (italics added) in future cost analyses."(Section 1 of the ICF Report) "This effect" is explained further in "[w]hile there is little doubt that this learning effect occurs, the learning estimates used by OTAQ [Office of Transportation and Air Quality] in its cost analyses are based on somewhat dated studies that are not specific to the mobile source sector." (Section 1 of the ICF Report)

Objective 3: "[T]o determine the best estimate of the effect of learning on costs in mobile source industries." (Section of the ICF Report)

Objective 4: "[T]o develop a reliable estimate of the effect of cumulative output" (Section 3.3 of the ICF Report)

SUMMARY OF THE REPORT

The Report contains two sections: summary and background and ICF Report. There is also a placeholder for an Appendix with peer review comments. The summary and background summarizes the findings of the ICF Report and provides a background about the EPA's need for the ICF Report.

The ICF Report reviews 53 studies on learning-by-doing, of which 20 are reviewed in detail. Subsequent to a description of how the subject matter expert and the relevant studies were chosen (Section 2), the ICF Report briefly discusses the concepts of learning curves and progress ratios (Sections 3.1-3.2) and summarizes the literature review (Table 1).

Section 3.4 presents an estimate of the average progress ratio for the mobile source sector (84.3% with a 95% CI: 83.9%-84.8%). This average is computed as the weighted average progress ratio from regression estimates of unit costs on cumulative output based on 5 studies in the mobile source sector. The inverse of the variance in the study is assigned as the weight.

It is well known that the rate of learning-by-doing varies across organizations and contexts. Section 4 discusses some aspects of such variation based on the literature review: (a) sources of such variation (b) depreciation of knowledge accumulated from learning-by-doing (c) the location of organizational knowledge (d) extensions of the conventional learning curves. This section also presents some examples of how learning curves have been applied.

Appendix A presents two methods for forecasting the change in unit costs due to learning-by-doing and Appendix B provides a summary of the reviewed articles.

REVIEW COMMENTS AND RECOMMENDATIONS

Unless otherwise stated, the recommendations can be readily made based on data reasonably available to the EPA.

Presentation and Organization

1. The overall presentation and organization of the Report is generally clear. However, there are some specific areas that require greater clarity. These are described below.

2. The Report and ICF Report appear to have multiple objectives that are stated in several places. In addition, there is at least one aspect that is provided in the Report but not mentioned as an objective (methods of forecasting in Appendix A). So, I recommend a short subsection somewhere that explicitly states the objective(s) in one location. In addition, I recommend that the document refer to these objectives consistently throughout the document. For instance, Objectives 3 and 4 above are similar but it is not clear what the difference between a "reliable" and a "best" estimate is. It may be more appropriate to choose one of them, and use that consistently. Also, note that the term "best estimate" has a generally accepted econometric definition as the estimate with the lowest variance among a set of estimates. Hence, it may be prudent to avoid using that term or clarify its meaning as used in this Report.
3. The two paragraphs beginning "Learning is a major source of…." (p.11-12 of the ICF Report) do not directly relate to "what are progress ratios" and appear out of place in that subsection. I recommend that they be moved to the next subsection on "Summary of Literature Review". Also see point 4 below.
4. The Report and the ICF Report do not seem to provide a clear summary of the literature review. The summary in the "Summary and Background" section of the Report focuses almost entirely on the estimation of the average progress ratio, which is only a small part of the review. The summary in the ICF Report (Section 3.3) is only a table with no additional explanation. I recommend that a more descriptive summary of the literature review be included. Among others, I suggest that the summary highlight the variation observed in the rates of learning-by-doing (currently discussed in Section 4 of the ICF Report). Also see point 14 below.
5. Section 1 of the ICF Report (paragraph 4) states "It will also summarize empirical estimates of the learning effect separately for each of the specific mobile source industries (e.g., original equipment auto makers, parts suppliers to those auto makers, loose engine manufacturers, large truck manufacturers, and nonroad equipment manufacturers) for which studies are found that address those specific sectors." This break-down by industry is not provided in the Report. The Report provides only one estimate for the entire sector. Hence, this statement should be corrected or placed in a different context (e.g., the original intent of the study was to summarize empirical estimates separately…). Also see point 15.
6. There is a minor typographical error on p.19 (ICF Report) at the beginning of the second paragraph.

Review Approach, Comprehensiveness and Appropriateness of Studies Included

7. The overall approach to the review---identifying studies of learning-by-doing in the mobile source sector, reviewing them for relevance to the goals of the study and identifying a

shorter list of relevant studies for more detailed review---appears reasonable. The list of topics included in the review and the coverage of those topics appear broadly reasonable.

8. The set of articles related to progress ratio estimation in the mobile source sector and included for review appears to be reasonably comprehensive. A search for articles on learning-by-doing in the mobile source sector on Google Scholar did not yield any new substantively-contributory articles on this subject. A possible, but not necessary, addition is Balasubramanian and Lieberman, 2011. The article itself is not relevant but the Online Appendix to this article contains estimates of new-plant learning-by-doing using different methods for several industries, at a more fine-grained level (at the SIC-4 level) than Balasubramanian and Lieberman, 2010. I attach the relevant portions of this article, with learning rates translated into progress ratios, as Appendix I.
9. Based on a broader search of articles on learning-by-doing, an article (Haunschild and Rhee, 2004) may potentially add some insights in Section 4.1, but not including it will not detract substantively from the findings of the Report. I have included the abstract in Appendix II.

Methodology and Conclusions Related to Estimation of Average Progress Ratio

10. The overall conclusion that learning-by-doing occurs in the mobile source sector is well-founded and largely indisputable.
11. The methodology for estimating the weighted-average progress ratio from 5 studies is broadly reasonable. In particular, the following executive decisions related to estimating the average progress ratio appear reasonable given the objectives of the Report:
    a. Focusing only on studies that examine unit costs and excluding studies that use other measures of performance
    b. Excluding studies of learning-by-doing in shipbuilding during the Second World War due to the uniqueness of the context
12. The Report uses a "fixed-effects" model to combine estimates from different studies (the weight is the inverse of the variance). However, it is not clear that all studies used the same method to computing standard errors. For instance, some studies may have computed heteroscedasticity-robust or clustered standard errors, which would typically be larger than studies that assume homoscedasticity. If that is indeed the case, taking a simple inverse would not be accurate, and presenting one or more alternative estimates in addition to this "fixed effects" estimate (e.g., a simple average) may provide a more complete picture. An additional rule can be applied if one of these estimates has to be chosen (e.g., the most conservative).
13. The methodology for estimating the standard error of the average progress ratio is not explicit in the Report. A sentence or two describing this should be added in Section 3.4.
14. Though the estimate of the weighted-average progress ratio is broadly reasonable, the discussion about the uncertainty associated with learning-by-doing is quite sparse. Such a

discussion is important for a full understanding of the weighted-average progress ratio. The standard error of the weighted-average progress ratio is likely to be small, as currently stated in the Report. However, that small standard error does not reflect the true variation in the progress ratios across organizations and contexts, which is likely to be significantly larger. Also, some important aspects of the studies need highlighting to provide readers a better understanding of their context (which could be possibly different from today's context or other contexts in the mobile source sector). Hence, providing a prominent contextual discussion in the Summary and Background section of the Report and in Section 3.4 of the ICF Report covering the following aspects is recommended:

a. There is significant variation and uncertainty in the rates of learning-by-doing depending on many factors, and that learning-by-doing is not automatic as discussed in Section 4 of the ICF Report
b. The specific empirical context of the 5 studies, *viz.* the production of a new car model, as well as the dates of these studies (where available).

These aspects are currently discussed in different places in the Report but it is important that a summarized version of these points be located close to discussions of the weighted-average progress ratio.

15. Section 2 of the ICF Report (p.4-5) provides two reasons for not providing a break-down of progress ratios by industry (see Appendix III for the list of industries in the mobile source sector). The first is the lack of studies in many of the individual industries and the second is the greater within-industry variation in rates of learning-by-doing as compared to inter-industry variation in those rates. Of these reasons, the first has merit. However, the second is not a valid reason for not providing a break-down by industry. It raises the question of why studies from outside the mobile source sector should not be used for estimating the "best" or "reliable" progress ratio for the mobile source sector. In my opinion, since there is significant variation across industries (albeit less than the within-industry variation) in the average progress ratios (e.g., see Appendix I to this review or Dutton & Thomas, 1984 cited in the Report), it is appropriate to consider using industry-specific estimates, *if and when such estimates become available.* In general, it will be more informative to use the means of two sub-groups than the mean of the group as a whole.
16. The Report aims to get a "best" or "reliable" estimate of the "effect" of learning-by-doing (or cumulative output) on costs. The term "effect" has a causal connotation. However, it is not clear that all five studies used econometric techniques to causally estimate the effect of learning-by-doing. If so, it may be more appropriate to characterize the estimated weighted-average progress ratio as the association between unit costs and cumulative output, rather than as the effect of learning on costs. This approach is also consistent with the decision to focus on models that include only cumulative output as a predictor instead of using a more

complete model that includes other factors. This decision implies that the effect of other factors is not isolated from the effect of cumulative output, when estimating the weighted-average progress ratio.

Methodology Related to Forecasting the Impact of Learning

17. Point 16 above also relates to the discussion in Appendix A. As discussed in the Report, cumulative output can be correlated with many other factors (e.g., economies of scale). Also, the estimated weighted-average progress ratio in Report uses models that include only cumulative output as a predictor. Hence, forecasting the impact of learning-by-doing alone based on that ratio is not possible in the absence of information on the other factors. However, this does not render the forecasting exercise provided in Appendix A meaningless. It still measures the likely change in unit costs due to a change in cumulative output, which could be due to learning-by-doing or due to other factors. Recognizing this assumption implicit in these methods is important, especially when applying these methods.

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APPENDIX I: PROGRESS RATIO ESTIMATES FROM BALASUBRAMANIAN AND LIEBERMAN, 2011

SIC and Description	Estimate (Olley-Pakes Method)
3537 Industrial Trucks, Tractors, Trailers & Stackers	85%
3711 Motor Vehicles & Passenger Car Bodies	89%
3713 Truck & Bus Bodies	82%
3714 Motor Vehicle Parts & Accessories	81%
3715 Truck Trailers	89%
3716 Motor Homes s	80%
3721 Aircraft	86%
3724 Aircraft Engines & Engine Parts	81%
3728 Aircraft Parts & Auxiliary Equipment, NEC	75%
3731 Ship Building & Repairing	90%
3732 Boat Building & Repairing	85%
3743 Railroad Equipment	84%
3751 Motorcycles, Bicycles & Parts	74%
3792 Travel Trailers and Campers	91%
3799 Transportation Equipment, NEC	85%

Source: Balasubramanian N. and Lieberman M., 2011. Learning by Doing and Market Structure. Journal of Industrial Economics. 59(2): 177-198, Online Appendix, Appendix III.

APPENDIX II: POTENTIALLY USEFUL RECENT STUDIES OF LEARNING

A. The Role of Volition in Organizational Learning: The Case of Automotive Product Recalls. Haunschild, Pamela R; Rhee, Mooweon. Management Science 50.11 (Nov 2004): 1545-1560.

What is the role of volition in organizational learning? Do firms learn better in response to internal procedures or external mandates? Existing literature provides conflicting answers to this question, with some theories suggesting that volition is important for learning because autonomy increases commitment and problem analyses, whereas external mandates tend to produce defensive reactions that are not coupled to the organization in any useful way. Yet, other theories suggest that mandate is important for learning because external pressures act as jolts that help overcome organizational inertia, resulting in deep exploration of problems to prevent future surprises. We investigate this issue in the context of automakers learning from voluntary versus involuntary product recalls. Using data on all recalls experienced by automakers that sold passenger cars in the United States during the 1966-1999 period, we follow the learning - curve tradition in investigating the effects of voluntary and involuntary recalls on subsequent recall rates. We find that voluntary recalls result in more learning than mandated recalls when learning is measured as a reduction in subsequent involuntary recalls. This effect is at least partly because of shallower learning processes that result from involuntary recalls. The results of this study suggest an important, yet understudied, determinant of the rate and effectiveness of learning - volition. The results also add to our knowledge of the different learning processes of generalist and specialist organizations.

APPENDIX III: DEFINITION OF MOBILE SOURCE MANUFACTURING SECTOR

It includes:

On-road vehicles and engines

Cars & Light Trucks

Heavy Trucks, Buses & Engines

Motorcycles

Nonroad engines, equipment and vehicles

Aircraft

Diesel boats and ships

Gasoline boats & personal watercraft

Nonroad diesel equipment (including excavators and other construction equipment, farm tractors and other agricultural equipment, heavy forklifts, airport ground service equipment, and utility equipment such as generators, pumps, and compressors)

Nonroad gasoline equipment (forklifts, generators & compressors)

Small gasoline equipment (lawn & garden)

Locomotives

Snowmobiles, dirt bikes & ATVs

UCLA Anderson
SCHOOL of MANAGEMENT

Marvin Lieberman
Professor of Strategy
Tel (310) 206-7665 Fax (310) 206-3337
marvin.lieberman@anderson.ucla.edu
http://www.anderson.ucla.edu/faculty/marvin.lieberman/

April 14, 2016

To Whom It May Concern:

I am a professor in the UCLA Anderson School of Management in Los Angeles, California. I was asked to review the report, "Cost Reduction through Learning In Manufacturing Industries and in the Manufacture of Mobile Sources," prepared for the U.S. Environmental Protection Agency. My comments on the report are attached to this letter.

My qualifications and expertise to review the EPA report are as follows. I have contributed to the literature on industrial learning curves and have followed that literature over many years. My PhD dissertation ("The Learning Curve, Pricing and Market Structure in the Chemical Processing Industries," Harvard University, 1982) focused on the nature and implications of learning in manufacturing industries. Two of my journal articles on industrial learning are described in the EPA report. In addition to my academic contributions in this area, I served as consultant to a number of companies in the chemical, energy and electronic sectors in the 1980s and 1990s, performing studies that used the learning curve concept to forecast manufacturing costs. I also served as subject matter expert to the RAND Corporation in preparing a report that surveyed the literature on learning curves in the energy sector (similar to the present report which focuses on the mobile source sector).

I have no real or perceived conflicts of interest in reviewing the EPA report. Other than the current review, I have not performed any consulting work relating to learning curves in more than 15 years. I have no connection to the EPA or to companies in the mobile source sector.

I spent a total of 27 hours to complete this task.

Sincerely yours,

Marvin Lieberman

Marvin Lieberman

THINK IN THE NEXT

110 Westwood Plaza, Suite B415, Gold Hall
Box 951481, Los Angeles, California 90095-1481

Review of "Cost Reduction through Learning In Manufacturing Industries and in the Manufacture of Mobile Sources," a report prepared for the Assessment and Standards Division, Office of Transportation and Air Quality, U.S. Environmental Protection Agency.

I have been asked to review this report for the EPA, with a focus on: 1) clarity of the presentation, 2) the overall approach and methodology, 3) appropriateness of the studies included and other inputs, 4) the data analyses conducted, and 5) appropriateness of the conclusions.

The EPA report "is intended to be a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically. It consists of a literature review of studies of learning in mobile source industries, most notably the automotive industry (both original equipment manufacturers and tier 1 suppliers); identifies and summarizes empirical estimates of learning from those studies; develops a methodology to estimate the impacts of learning in the mobile source sectors using the quantitative estimates obtained from the literature review; and develops a best estimate for learning in the mobile source sector."

Thus, the report aims to provide "a single compendium study on industrial learning in the mobile source sector" (p. 1) which can serve as a source document for the EPA and other organizations. It is my understanding that beyond compiling evidence on the prevalence of the learning curve phenomenon across a range of mobile source manufacturing environments, a key objective is to identify a representative learning rate or "progress ratio" in the mobile source sector that could be incorporated into future cost analyses and rulemaking by the EPA.

I find the report to be comprehensive, and I believe it does a good job of characterizing the rates of learning typically found in transportation equipment manufacturing plants. Dr. Linda Argote of Carnegie Mellon University, the Subject Matter Expert for the report, is widely regarded as the world expert on industrial learning curves, having published numerous research studies in this topic area and a major book, *Organizational Learning* (now in second edition), which provides a critical summary and guide to findings in the literature. Compared with this book or any individual research study, the EPA report offers a more in-depth view of the literature on industrial learning that is most relevant to the mobile source sector. Overall, I find the report to be a well-executed document that is likely to be helpful in providing a basis for incorporating forecasts of learning into EPA and other government rulemaking.

Despite these strengths of the report, I believe it has a number of limitations that should be (more clearly) acknowledged. I also see several areas where improvements can be made in the document.

In my initial comments (points #1 through #4 below), I focus on the "summary" sections of the report, which are likely to be the most widely read material. (This summary material appears in two places: at the beginning of the initial "Summary and Background" section as well as pages 19 and 20 of the report.)

(1) While the report surveys a substantial amount of literature, the summary is based upon five representative studies of manufacturing assembly plants that were "used as the basis to estimate the progress ratio for the mobile source sector." These five studies include one on the manufacture of commercial aircraft, three on the manufacture of trucks, and one on passenger cars. Averaging across these studies, the bottom line estimate from the report is that: "the recommended progress ratio is 84.3 percent, with a 95% confidence interval of 83.9 percent to 84.8 percent."

I agree that the weighted average progress ratio across the five selected studies is 84.3 percent. Moreover, based on my experience and my reading of the broader literature on learning curves, this is not an unreasonable figure for manufacturing cost projections and forecasting in the mobile source sector (at least for plants of the type surveyed by the five studies - see points #2 and #3 below).

However, the claim that there is "a 95% confidence interval of 83.9 percent to 84.8 percent" is misleading, in my opinion. That statement of the confidence interval overstates the precision of the estimate. Let me explain.

The method used in the report to compute the confidence interval is appropriate if there were some underlying, universal rate of learning in the mobile source sector. In this case the individual studies provide independent estimates of this "true" rate of learning, with the specific values obtained by each study being subject to random error. As we add more studies, the errors wash out, and the mean of the estimates converges on the true universal value. Under these assumptions, it would be appropriate to use the standard errors of the individual studies to determine the precision of the mean in denoting the "true" rate of learning (as is done in the report to establish the "confidence interval").

However, it seems very unlikely that there is a single, universal rate of learning in the mobile source sector. Even among the five studies included in the final sample, there is some evidence that the learning curve is steeper in aircraft and automobile manufacturing (both of which show progress ratios of 82% in the studies) than in truck manufacturing (which show progress ratios of 86% or 87%). Thus, the progress ratio does seem to show variation across products in the sector. Moreover, studies described elsewhere in the report make it clear that the rate of learning is subject to managerial influence. Such variation across manufacturing environments does not imply that it is inappropriate to use an average value (e.g., a progress ratio of 84.3%) for forecasting purposes. But it does mean that we should not regard the 84.3% progress ratio as some kind of precise and universal standard in the sector.

Rather than taking the (weighted) average value of 84.3% across the five studies, if one chose to be more conservative, a reasonable choice would be to use the smallest rate of learning in the sample, i.e., the progress ratio of 87%. In any case, the estimates from these five studies all lie in a fairly close range. Depending on the purpose at hand, one could justify using 84.3%, or 87%, in my opinion.

(2) All five of the plants that are studied in this sample are engaged in final assembly of transportation equipment (trucks, automobiles and airplanes). Thus, the progress ratio estimates are indicative of plants of this type, i.e., assembly plants for relatively complex mechanical products made on a production line. The estimates may not be suitable for plants producing other types of products or plants using other types of processes. For example, the article by Nykist and Nilsson (2015) cited on page 41, which surveyed dozens of studies on learning in the production of Li-ion battery packs, found a learning rate of only 9% for the overall industry and 6% for the leading manufacturers. (Presumably, these figures correspond to progress ratios of 91% and 94%.) This is a much lower learning rate than the 84.3% progress ratio observed on average across the five selected studies.

(3) A further deficiency in the presentation of this material (in the summary and recommendations section as well as the broader report, e.g., Section 3.3., bullet #5) is the failure to point out that the progress ratio estimates in the five selected studies are not based upon the total cost of production. As noted above, all five studies in the final sample focus on assembly plants for transportation equipment. None of the studies utilizes data on the *total* costs per unit of output in these plants. Rather, four of the studies focus on labor costs and labor productivity in the assembly plant (vehicles produced per labor hour, or labor hours per aircraft), and one study focuses on defect rates.

An 84.3% progress ratio based on labor cost reflects a 15.7% savings in labor cost per unit for each doubling of cumulative output. It does not imply a 15.7% savings in *total* cost per unit for each doubling. Consider a truck assembly plant where 80% of the final cost of a truck is the cost of purchased components. In this case, the estimated 84.3% progress ratio applies only to the value added at the plant, i.e., the 20% of total cost above that of the component parts. (Over time, these proportions will change slightly as the amount of assembly labor input declines.) If the component parts used in the truck are conventional parts that have long been made in high-volume and require little or no redesign for the vehicle being produced, one would see little cost reduction for the parts over time due to learning. In this case, a learning curve applied to data on *total costs per truck* would show a much smaller rate of cost reduction than the 84.3% progress ratio, which applies only to the final assembly labor. (Note that if total employment in the plant does not change as output increases over time, this progress ratio also applies to the per-unit cost of property, plant and equipment at the assembly plant).

Thus, any forecast of reduction in total unit cost depends on (1) the progress ratio multiplied by the growth in cumulative output (number of "doublings") in the assembly plant, as well as (2) the progress ratio and change in cumulative volume applicable to the production of the component parts. In my opinion, the report should be clear about this need to consider cost reduction of the component parts as well as the learning curve in the final assembly plant. If a new vehicle model is produced with new component parts, the rates of cost reduction for parts production and final assembly are likely to largely coincide (so that a single progress ratio can be used), but this need not be the case.

Similarly, the report is unclear (and, I think, misleading) in describing the nature of the cost analysis in the five representative studies. The first paragraph of the "Results and Recommendations" section on page 19 states: "Because the focus of our analysis is on manufacturing costs, we included studies that used unit costs or variables closely related to costs, such as the number of units produced or defects per unit, as the dependent variable." As I have indicated above, the "unit costs" analyzed in the five studies are essentially labor costs, or unit costs of final assembly, *per se*. The studies do not tell us the extent to which the total cost per unit, including the cost of the component parts, followed a similar progress ratio.

(4) Given that the final recommendations in the report are based almost exclusively upon the five selected studies, it is useful for a reader to be able to review a detailed summary of these studies. Four of the studies are summarized in Appendix B. However, the (truck plant) study by Argote, Epple, Rao and Murphy (1997), does not seem to be included in Appendix B. I recommend that a summary of this study be added the appendix.

Moreover, it might be helpful to add some additional information to Table 2, which very briefly summarizes the five selected studies. This information might include the dependent variable. (Alternatively, the report could point out in the text that the Levitt et al. (2013) study is different from the others in that it uses defect rates as the dependent variable. While this can be determined from Table 1 and the discussion of Levitt et al. (2013) later in the report, it is awkward for a reader to have to search and scan between these various sections.) Table 2 might also indicate the pages in the appendix where the summary of each study can be found.

Points 5 through 12 below apply to the literature review, which covers six topic areas in subsections 4.1 through 4.6 of the report. In general, I find the literature review to be comprehensive and informative. I comment on each subsection separately.

<u>Section 4.1. Sources of learning variation</u>

(5) One issue raised in this section is the distinction between the learning curve and economies of scale. Various studies distinguish between the two concepts and provide estimates on the magnitude of each effect. (At the bottom of page 22 this

distinction is called “a new development and learning curve theory.” However, studies have made the separation between learning and scale economies for decades now, so I would not call it a “new development”.)

I agree that when possible, the two effects should be estimated separately. However, the typical progress ratios described in the report incorporate the impact of economies of scale within the overall learning effect. Thus, the report provides no guidance on how to perform a cost analysis forecast that incorporates learning and economies of scale as separate elements. Perhaps the text should be more explicit about this, although the last paragraph of section 3.3 (“Column 6 – type of outcome variable”) makes it clear that the report is focused on using only cumulative output as a predictor.

When controls for economies of scale are omitted from the analysis, the estimated progress ratio includes the effects of both learning and scale economies. This has been shown in a number of studies (including my 1984 article on chemical products). Adding a separate parameter for economies of scale normally improves the statistical fit, but the improvement is seldom dramatic, and most studies have found scale economies to be less important than the learning effect. Moreover, if the data sample is small, colinearity between the learning and scale parameters can reduce the accuracy with which each is estimated. One implication is that if the analyst or policy maker is able to apply only a single cost driver for forecasting purposes, application of a learning curve or progress ratio to forecasted cumulative output may provide the best projection of future costs.

(6) I am puzzled that the findings in my study with Balasubramanian (2010) are heavily discounted because the learning rate “was estimated using revenues less materials costs (i.e., value added) as the outcome variable, rather than unit cost.” As indicated in point #3 above, none of the five studies selected as representative of the mobile source sector actually utilize data on unit cost. Rather, four of the studies use data that correspond to value added in final assembly, omitting materials costs. Thus, the dependent variable in Balasubramanian and Lieberman (2010) is not so different from that of the selected studies. (However, Balasubramanian and Lieberman estimate a learning rate over the life the manufacturing plant, rather than over the life a new product within the plant.)

Balasubramanian and Lieberman (2010) develop estimates of learning rates by SIC code, including many industries in the mobile source sector. The findings show that learning rates differ significantly across industries and sectors. The estimated progress ratios identified by Balasubramanian and Lieberman (2010) for industries in the mobile source sector, by three-digit and four-digit SIC code, are as follows:

	Estimated Progress Ratios: OP	ACF
371 MOTOR VEHICLES AND MOTOR VEHICLE EQUIPMENT	80%	79%
372 AIRCRAFT AND PARTS	81%	87%
373 SHIP AND BOAT BUILDING AND REPAIRING	89%	93%
374 RAILROAD EQUIPMENT	79%	89%
AVERAGE:	82%	87%

	Estimated Progress Ratios: OP	ACF
3711 MOTOR VEHICLES AND PASSENGER CAR BODIES	89%	86%
3713 TRUCK AND BUS BODIES	82%	90%
3714 MOTOR VEHICLE PARTS AND ACCESSORIES	81%	78%
3715 TRUCK TRAILERS	89%	90%
3716 MOTOR HOMES	79%	76%
3721 AIRCRAFT	86%	93%
3724 AIRCRAFT ENGINES AND ENGINE PARTS	81%	89%
3728 AIRCRAFT PARTS AND AUXILIARY EQUIPMENT, N.E.C.	75%	83%
3731 SHIP BUILDING AND REPAIRING	90%	98%
3732 BOAT BUILDING AND REPAIRING	85%	89%
3743 RAILROAD EQUIPMENT	83%	87%
AVERAGE:	84%	87%

Estimates in the two columns above are based on two different procedures (OP and ACF) for correcting potential endogeneity in the data.

I show these estimated progress ratios, not to have them included in the EPA report, but rather to indicate that the average learning rates for industries in the mobile source sector, as estimated by Balasubramanian and Lieberman (2010), are substantially in line with those in the summary section of the EPA report.

[In the attached Appendix, I give more detail on these progress ratios and their derivation from the industry-specific learning rate estimates reported by Balasubramanian and Lieberman (2010).]

Section 4.2. Knowledge persistence and depreciation

(7) This section does a good job of characterizing studies of the learning effect that have considered knowledge depreciation. The differences in the estimated depreciation parameter across the various studies are striking. Perhaps the best

explanation for these large differences is provided by the summary of Agrawal and Muthulingam (2015), which appears in section 4.4 (as well as partly in section 4.2): "the rate of knowledge depreciation depends on where knowledge is located…."

One confusing element in this section is that some of the depreciation rates are monthly and others are annual. On pages 27 and 28, for example, the text might clarify that Benkard and Argote's estimates are *monthly* rates of depreciation (although the figures are converted to an annual basis in table 3).

Section 4.3. Knowledge transfer and spillovers

(8) This section is effective in describing research findings relating to knowledge transfer across organizational units (additional shifts, new models, etc.) *within a given firm*. However, the section ignores the existing literature on knowledge transfer and spillovers *across firms* (except for very brief mention in footnote 5). This literature on inter-firm spillover of learning is fairly extensive, although the evidence is based mostly on studies using data outside the mobile source sector.

Section 4.4. Location of organizational knowledge

(9) This section is informative and well done. Indeed, I think it would be helpful to provide some of this material earlier in the report - specifically, to make it clear that learning and knowledge can be embedded in people, in organizational routines, or in technology/physical capital. The fact that accumulated knowledge can be embedded in these three ways – which are each quite different - is fundamental to gaining an understanding of the differences found across studies with respect to knowledge depreciation, knowledge transfer, and (potentially) industry-specific rates of learning, which are discussed in the previous sections of the report. Although this decomposition of the location of organizational knowledge has only recently been fully documented in studies of learning, it has been generally recognized for some time.

Section 4.5. The specification and aggregation of learning

(10) This seems to be a residual section in the report; many key issues relating to the specification and aggregation of learning have already been discussed in previous sections. Thus, Section 4.5 does not truly serve a standalone function; rather, it seems to be a placeholder to summarize three studies that were otherwise hard to classify. Perhaps the section should take a broader perspective, summing up many of the conclusions of the previous sections that relate to the specification and aggregation of learning.

(11) One specification issue that is left hanging in the report is whether the learning curve should be estimated with an initially "steep" portion followed by a "flat"

portion (once the data have been transformed into logarithms). This specification issue is raised on the last page of the Summary and Background section; however, there is no specific follow-up in the report. (Virtually all of the presentation in the report is consistent with a single learning curve that does not change slope over time.) This issue of whether the slope of the learning curve is constant or diminishing should be discussed, and ideally, resolved in the report.

<u>Section 4.6. Application of the learning curve</u>

(12) The studies summarized in the section are quite diverse. Nevertheless, it seems appropriate to have a concluding section to consider these studies.

As noted in point #2 above, it is striking that Nykist and Nilsson's (2015) survey found learning rates for production of automotive Li-ion battery packs to be substantially smaller than the 84.3% progress ratio that the EPA report proposes for cost forecasting in the mobile source sector. It would be informative to consider possible sources of this large discrepancy in learning rates between Li-ion battery manufacturing and transportation equipment final assembly.

<u>Typographic errors and other minor corrections</u>

In the *title of Summary Table 1*, "Progress Rations" should be Progress Ratios".

Summary and Background, page 3. In the middle paragraph, "for each doubling of production volume" should be "for each doubling of cumulative production volume". In the sentence that follows, "it was assumed that production volumes would have doubled" should be "it was assumed that cumulative production volumes would have doubled".

Page 19. "In error! Reference source not found" is a typographical error.

Respectfully submitted,

Marvin Lieberman

Los Angeles, California

April 14, 2016

APPENDIX

Estimated Progress Ratios for Mobile Source Industries by SIC Code, Based on Balasubramanian and Lieberman (2010)

	SIC	OLS		OP		ACF			Estimated Progress Ratios:		
		Coeff.	Std Error	Coeff.	Std Error	Coeff.	Std Error		OLS	OP	ACF
371 MOTOR VEHICLES AND MOTOR VEHICLE EQUIPMENT	371	0.191	(0.01)	0.323	(0.03)	0.332	(0.04)		88%	80%	79%
372 AIRCRAFT AND PARTS	372	0.157	(0.02)	0.298	(0.05)	0.194	(0.09)		90%	81%	87%
373 SHIP AND BOAT BUILDING AND REPAIRING	373	0.108	(0.02)	0.167	(0.04)	0.104	(0.04)		93%	89%	93%
374 RAILROAD EQUIPMENT	374	0.144	(0.05)	0.335	(0.14)	0.172	(0.10)		91%	79%	89%
								AVERAGE:	90%	82%	87%
3711 MOTOR VEHICLES AND PASSENGER CAR BODIES	3711	0.127	(0.03)	0.174	(0.07)	0.215	(0.07)		92%	89%	86%
3713 TRUCK AND BUS BODIES	3713	0.192	(0.02)	0.289	(0.05)	0.152	(0.07)		88%	82%	90%
3714 MOTOR VEHICLE PARTS AND ACCESSORIES	3714	0.177	(0.01)	0.301	(0.03)	0.351	(0.03)		88%	81%	78%
3715 TRUCK TRAILERS	3715	0.098	(0.03)	0.169	(0.05)	0.149	(0.06)		93%	89%	90%
3716 MOTOR HOMES	3716	0.166	(0.04)	0.333	(0.09)	0.395	(0.16)		89%	79%	76%
3721 AIRCRAFT	3721	0.055	(0.05)	0.214	(0.12)	0.098	(0.08)		96%	86%	93%
3724 AIRCRAFT ENGINES AND ENGINE PARTS	3724	0.159	(0.03)	0.305	(0.09)	0.170	(0.11)		90%	81%	89%
3728 AIRCRAFT PARTS AND AUXILIARY EQUIPMENT, N.E.C.	3728	0.188	(0.02)	0.424	(0.06)	0.269	(0.08)		88%	75%	83%
3731 SHIP BUILDING AND REPAIRING	3731	0.054	(0.02)	0.157	(0.05)	0.023	(0.04)		96%	90%	98%
3732 BOAT BUILDING AND REPAIRING	3732	0.134	(0.02)	0.234	(0.04)	0.166	(0.04)		91%	85%	89%
3743 RAILROAD EQUIPMENT	3743	0.138	(0.04)	0.264	(0.09)	0.205	(0.08)		91%	83%	87%
								AVERAGE:	91%	84%	87%

CHICAGO BOOTH

The University of Chicago Booth School of Business

Chad Syverson
J. Baum Harris Professor of Economics

5807 South Woodlawn Avenue
Chicago, Illinois 60637
Telephone: (773) 702-7815
chad.syverson@chicagobooth.edu

April 7, 2016

Jennifer Richkus, Research Environmental Scientist
RTI International

Dear Ms. Richkus:

Please find enclosed my peer review of the report "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources."

By way of background, I am the J. Baum Harris Professor of Economics at the University of Chicago Booth School of Business. I obtained a PhD in Economics from the University of Maryland in 2001 and have been on the faculty at the University of Chicago since that time. Regarding my specific qualifications and expertise as a peer reviewer for this report, I have conducted extensive research and published multiple peer-reviewed articles on the productivity of plants, companies, and industries within the manufacturing sector. I also coauthored a peer-reviewed study investigating the qualitative and quantitative nature of learning by doing in the automobile industry. Indeed, this study is reviewed in the report and one of the five used to derive the "bottom line" learning rate discussed therein.

I have read the report thoroughly and offer in the enclosed review my opinion of how well it achieves its intended goal of being, as stated in my charge letter, "a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically." My impressions were primarily formed based on the following aspects of the report: 1) clarity of the presentation, 2) the overall approach and methodology, 3) appropriateness of the studies included and other inputs, 4) the data analyses conducted, and 5) appropriateness of the conclusions.

As was also requested in the charge letter, I am informing you that I spent an estimated 20-25 hours of total work time reading the report, examining various supplementary materials, and preparing this review.

Sincerely,

Chad Syverson
Enclosure

Review of "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources"

Purpose and Charge

I have been asked to provide peer review of the report "Cost Reduction through Learning in Manufacturing Industries and in the Manufacture of Mobile Sources," which has been prepared by ICF International for the U.S. Environmental Protection Agency. My charge is to determine how well the report achieves its intended goal of being "a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically." I conducted this evaluation with five general criteria in mind: 1) clarity of the presentation, 2) the overall approach and methodology, 3) appropriateness of the studies included and other inputs, 4) the data analyses conducted, and 5) appropriateness of the conclusions.

Overall Assessment

On balance, the study is a very fine review of the literature on learning by doing in general, but especially with regard to its manifestation in manufacturing operations during the past few decades. The report is notably comprehensive within this scope, makes sensible topical categorizations in its discussion of the literature's findings, and is clearly written.

The report does an excellent job of sorting through the large research literature to focus on studies that are most germane to its mission. First, its classification of works into parts that receive more cursory reviews as opposed to more comprehensive ones is very sensible; there is no paper in the former category that I think clearly belongs in the latter. Second, the five particular studies from which the report extracts its "meta-estimate" of the learning rate for mobile source manufacturing also appear to be well chosen based on the report's quantitative objective. The meta-estimate—a progress ratio of 84% (each doubling of cumulative experience reduces productivity, e.g. unit costs, by 16%)—strikes me as quite plausible, though I have some questions about the associated reported precision that I detail below.

I expect that this study will serve EPA's needs well, as best as I understand those needs. The report is also comprehensive and detailed enough to be able to serve as an academic resource. It will function nicely both as a map of the literature for researchers seeking to learn more and as a teaching guide for related coursework.

In sum, it is my opinion that the report does achieve the intended goal of being a definitive, reliable, single source of information demonstrating the occurrence of learning in general and in the mobile source industry specifically.

Specific Comments, Questions, and Suggestions

- The report extensively discusses "forgetting," the depreciation of the experience stock, at least in terms of the contribution of that experience to productivity gains. This discussion is appropriate, as several empirical studies have found evidence of simultaneous learning and forgetting. Knowledge depreciation appears to be part of reality in many production settings.

  The review of the empirical estimates of forgetting rates is conducted in isolation from the review of learning rates estimates. To the extent that one objective of the study is to identify the expected pace at which mobile source manufacturing productivity should improve with production experience, though, it seems to me that what matters in the end is the net effect of learning and depreciation rather than the gross learning rate.

  I recognize the gross-versus-net distinction might not be easy to quantitatively reconcile. The particular ways depreciation is parameterized in the literature does vary across papers, clouding the mapping from the estimated depreciation rates to the expected value in mobile source manufacturing. It is definitely more complicated than comparing the standard log-cost, log-experience bivariate gross learning rate regressions as the report does now. (Though of course even in that case things are not perfectly comparable across settings.)

  Therefore it might not be possible to derive a bottom-line net learning rate parameter that is as comparable and applicable as the gross parameter the study reports now. However, it does seem prudent to at least discuss the net-versus-gross distinction and how it might matter when applying the findings of the report to practical settings.

  I realize that the study argues that mobile source manufacturing has several properties (production typically is conducted at an even rate, learning is often embedded in technology and routines, and the sector experiences relatively modest worker turnover) that make it likely that depreciation would tend to be on the low end of estimates in the literature. This does not seem unreasonable. However, arguing that these effects are likely to be smaller than usual does not necessarily imply depreciation is likely to be zero. Again, there might not be any easy practical alternative here in terms of quantitative reports, but it is worth discussing the issue.

- The only recent paper on learning by doing in manufacturing that I know about but did not see discussed in this study is Hendel and Spiegel (*American Economic Journal: Applied Economics*, Jan. 2014).

  Unlike many other papers in the literature, it breaks down an overall cost-reduction trend into components explained by investment and an incentive plan while also identifying residual gains likely achieved through traditional learning channels. Perhaps this paper is applicable to Section 4.5 due to its attempt to distinguish among types of learning (or more accurately, distinguish other time-trend productivity drivers *from* learning).

  That said, the paper's setting is not in mobile source manufacturing, and I think it is still a judgment call whether the paper warrants any more attention than a cursory review for the purposes of this study. In any case, I thought I would mention it.

- There are several points in the report where contrasts are made between measures of the outcome variable in learning by doing estimation. The report rightly points out (e.g., page 13, though see my comment on demand further below) that using price or any metric that embodies price is likely to confound supply-side learning effects with demand-side changes that could be unrelated to the learning process.

  This concern applies to value added, for example. However, it applies equally to shipments as an outcome variable. The report holds out shipments as problematic because they include any inventory accumulation or de-accumulation, and that is true, but shipments are also reported in real dollar values, raising the supply-versus-demand conundrum. This fact was not always made clear in the text. For example, when shipments are mentioned on page 13, only the inventory issue is raised, and moreover the output measure of Bahk and Gort (1993) is described as "the number of shipments." Perhaps I am just interpreting the wording differently than the sense in which it was meant, but this sounds like a quantity of units of a good rather than a dollar value.

- I have a couple of comments about the standard error of the "meta-estimate" calculated in the report. First, it would be helpful if the report offered a brief explanation of how this standard error is calculated from the literature's values cited in Table 2. While the point estimate of -0.245 is described as an inverse-variance-weighted average of the five point estimates, the standard error is left unexplained. If the calculation is complex, it need not be spelled out line-for-line; a short description of the calculation's intuition would be enough. (I made my own quick guess at a calculation: I assumed the only variation in the standard errors across the five papers was due to sample sizes and then calculated the total effective sample and hence the implied standard error across the five papers. That came out to the same 0.0039 reported in the study. Maybe I was lucky. In any case, some sort of guidance for the reader would be useful.)

  Second, and more substantively, is the possibility that the standard errors across the five studies in Table 2 vary for reasons besides just sample size differences. There are, after all, some basic differences across the studies: industry, outcome measure, etc. In some ways—and the report notes this—the fact that despite these differences their estimates are all markedly similar might suggest inferring that any heterogeneity across the studies is more or less orthogonal to the learning rate. On the other hand, it is not practically possible to statistically reject heterogeneous parameters with respect to covariates like industry, outcome measures, etc., with only five observations. As with the gross-versus-net distinction discussed above, I do not know if there is any straightforward way to quantitatively address this issue, but again it strikes me as something worth discussing a bit more in the report.

- I struggled to understand how the work of Laitner and Sanstad (2004) fit into the discussion. I realize that there might be learning about products among consumers, but it wasn't exactly clear to me from the description of their paper how this would influence supply-side learning. My best guess of the story is that demand-side learning affects the equilibrium quantity of a product, and that can change how quickly experience is accumulated on the supply side. If that is correct, though, then it is less clear to me that one would necessarily want to purge demand-side influences from learning estimation, as asserted in the price-as-an-outcome issue discussed above. Is there a fundamental difference between that point and the Laitner and Sanstad (2004) analysis?

- I completely agree with the study's interpretation of the literature that heterogeneity in learning rates could well be large across organizations, even within an industry, than across industries. This is a very useful point to make.

Typos and Minor Edits

- There is a missing closed parenthesis in the first sentence of EPA summary.
- There is what looks to be a LaTex citation error on page 19. From the context it appears to be a reference to Table 2.
- On page 49 in the appendix, the "review of the literature" progress ratio is cited as 83%, but the estimate given in the main body of the review is 84%.
- The Levitt, List, and Syverson study is cited as being published in both 2012 and 2013 in different locations. Also, on page 38, Levitt, List, and Syverson is described as studying the repair rate as an outcome variable rather than the defect rate.