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Learning by Doing in Multiproduct Manufacturing: Variety, Customizations, and Overlapping Product Generations

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Abstract. Extending research on organizational learning to multiproduct environments is of particular importance given that the vast majority of products are manufactured in such environments. We investigate learning in a multiproduct facility drawing on exceptionally rich data for a manufacturing firm that is a leading producer of high-technology hardware components. Weekly data for 10 years from the firm's production and human resource tracking systems are augmented by surveys of managers and engineers and by extensive firsthand observation. We find that productivity improves when multiple generations of the firm's primary product family are produced concurrently, reflecting the firm's ability to augment and transfer knowledge from older to newer product generations. No significant transfer of knowledge is evident between the primary product family and other products. Productivity is, however, adversely affected when the production facility is faced with extensive within-product buyer-specific customizations. We develop the implications of these findings for theory and practice.

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1. Introduction

Organizational learning and knowledge transfer are key to any firm's competitive advantage (Kogut and Zander 1992, Argote and Ingram 2000). Yet learning and knowledge transfer in a multiproduct production setting are not well understood. The production and operations management literature largely emphasizes that the production of a variety of products is harmful to productivity. At the same time, the organizational learning literature suggests that there can be benefits to learning from producing heterogeneous products. These differences in perspectives on product heterogeneity can, to some extent, be traced to differences in the nature of such heterogeneity. In this paper we leverage facility-level production data to unpack the nature of product heterogeneity in that facility and the implications of that heterogeneity for organizational learning and knowledge transfer.

This work investigates organizational learning and knowledge transfer in a U.S.-owned overseas manufacturing facility that is a leading producer of high-technology hardware components. The firm produces five generations of high-volume focus products as well as several nonfocus products that vary widely from the focus products in form factor and market application and are produced in relatively small volumes. The firm also undertakes thousands of variations of products to meet individual buyer specifications. We draw on 10 years of firm archival data, along with qualitative survey and observational data collected at the site, to develop insights into the acquisition and transfer of knowledge within and across product generations. Our analysis employs weekly data on five generations of a focus product, including the thousands of variations tailored to buyer specifications, as well as data for the suite of heterogeneous small-volume products produced by the firm. These data, coupled with information from surveys and interviews with managers, engineers, and trainers, enable us to understand the differential effects on knowledge acquisition and transfer of contemporaneous variation in product types as well as intertemporal variation as technological advances bring new products into the firm's repertoire.

Our results reconcile differences between the organizational learning and production and operations management literatures by identifying both advantages and disadvantages to product heterogeneity on the production line, depending on the extent and nature of product differences. We find that productivity improves when multiple generations of the same product are produced in the same facility. This positive impact on productivity of having multiple generations of the same product on the line is explained in part by the firm's ability to transfer knowledge rapidly from older to newer generations of the product and thereby improve long-term productivity. By contrast, we find productivity is decreased both when the production line is faced with product types that are quite different from each other and when faced with increases in buyer-specific product variations.

2. Theoretical Motivation

2.1. Organizational Learning

Learning curves have been found within many organizations and serve as a valuable indicator of the extent to which organizational performance improves with experience (Lapré and Nembhard 2010, Argote et al. 2003). Learning has been found in a breadth of industries from service industries, such as pizza franchises and booksellers (Darr et al. 1995, Ton and Huckman 2008), to a variety of manufacturing settings, such as semiconductors, airplanes, ships, and trucks (Argote et al. 1990, Epple et al. 1991, Benkard 2000).

The classic form of this organizational learning curve is given as

$$y_t = aQ_{t-1}^{b} \tag{1}$$

and is often written for estimation purposes in logarithmic form:

$$\ln y_t = c + b \ln Q_{t-1}, \tag{2}$$

where y is the unit cost or number of labor hours of units to produced at time t, a is cost or the number of labor hours required to produce the first unit, c is a constant equal to $\ln(a)$, Q is the cumulative number of units through time period t, b is the learning rate, and t is a time subscript (Argote 2013). In addition to unit costs, other metrics such as defects per unit or waste per unit (Lapré et al. 2000) have been shown to follow a learning-curve pattern. Thus, y can represent different performance metrics that vary, and generally improve, with experience.

Dutton and Thomas (1984) reviewed learning rates from more than 100 production programs and found that they differ widely not only across different industries, processes, and products but also within the same or similar processes and products. These observations have stimulated research focused on determining reasons for the variation in learning rates.

The knowledge accumulated from learning is embedded in various retention bins or repositories. According to Walsh and Ungson (1991), knowledge within a firm can be embedded in its people, its processes, its technology, or its structure. Although the number of repositories varies in different conceptualizations of organizational memory, all conceptualizations distinguish between knowledge embedded in individuals and knowledge embedded in the organization, including its processes, technologies, and structures.

The ability of a firm to transfer knowledge effectively across these elements within its own organizational boundaries can be a key element of competitive advantage (Argote 2013, Argote and Ingram 2000). Past research has quantified the amount of knowledge transfer across boundaries in the case of ship production (cross-location transfer), truck production (cross-shift transfer), and aircraft production (cross-product transfer) by modifying the experience term in the classic learning model to include a transfer parameter (Argote et al. 1990, Epple et al. 1996, Benkard 2000).

2.2. Learning Across Products

The majority of organizational learning studies focus on production of a small number of products with minor variations, including aircraft, ships, trucks, and automobiles (Alchian 1963, Rapping 1965, Argote and Epple 1990, Levitt et al. 2013). Yet 87% of U.S. output comes from multiproduct firms, and over half of all U.S. firms alter their product mix frequently (Bernard et al. 2010). Research that examines learning and product heterogeneity shows both advantages and disadvantages to an increase or change in product variety. A consensus has not emerged as to when heterogeneity helps and when it harms firm performance.

The productivity benefits associated with individual worker specialization were noted as early as Adam Smith (Smith 1776).[1] Indeed, production and operations management largely starts from the assumption that product variety increases production costs. Results from this literature show that changeovers in a multiproduct environment can be costly as a result of operators forgetting in the time in between working on same products (Shtub et al. 1993) and in the time to switch tools or molds (Womack et al. 1990). An increase in the variety of products produced on one line also complicates task scheduling, the planning of material handling and inventory, and quality control (Fisher and Ittner 1999).

Studies have shown different ways to mitigate the negative impacts of product heterogeneity. Designing products with shared components (Fisher et al. 1999), products that have commonality in their designs (Desai et al. 2001), or products that implement a modular design or have components that can be reused (Suarez et al. 1995) can improve productivity on a production line that handles a mixture of products. Lean manufacturing and flexible manufacturing systems also implement methods to allow a production line to handle a variety of products efficiently (Suarez et al. 1996, MacDuffie et al. 1996, Gaimon and Morton 2005, Suarez et al. 1995, Randall and Ulrich 2001). Goyal and Netessine (2011) investigated differences between product flexibility and volume flexibility in the context of response to demand uncertainty and found that adding volume flexibility to existing product flexibility is always beneficial but that the converse is not always true. An analysis of survey data of automotive manufacturing plants spanning 1999–2007 by Gopal et al. (2013) found that the high costs of new product introductions could be reduced by launching new products at plants with experience in related platforms. These studies on flexible systems characterize the different types of flexibility these systems can handle yet do not address long-term implications for learning or knowledge development that arise from these product differences.

Despite this focus in the production and operations management literature on mitigating product variety and the harmful implications thereof, not all empirical studies find a negative impact from an increase in product heterogeneity. Indeed, the literature on organizational learning suggests that product heterogeneity can lead to positive outcomes. Past work on accidents in the airline industry suggests that in the case of learning from errors, organizations learn more from diverse than homogeneous experiences (Haunschild and Sullivan 2002). In manufacturing industries, Bernard et al. (2010) suggested that product switching (measured as the mix of five-digit Standard Industrial Classification codes) contributes to a reallocation of resources within firms toward their most efficient use, as firms evolve their outputs to address changing industry dynamics. Additionally, Wiersma (2007) found that heterogeneity in related products had a positive impact on the learning rate within the Royal Dutch Mail.

More recent work has begun to unpack further under what conditions product variety might be expected to have positive versus negative implications for productivity. Work by Staats and Gino (2012) on the Japanese banking industry found the impact of variety on worker productivity to differ depending on whether a worker experienced the variety within a single day or across several days. Specialization of tasks within a single day increased worker productivity. However, variety (switching tasks) over the course of multiple days improved productivity of the same workers. In addition, workers who experienced higher variety stayed longer at the firm than those experiencing lower variety. Boh et al. (2007) found that diverse experiences in related systems played the largest role in improving productivity in software development groups and organizational units, whereas specialized experience had the greatest impact on productivity for individual developers. A laboratory study performed by Schilling et al. (2003) similarly found that group learning rates were significantly greater under either conditions of related variation than under conditions of specialization or unrelated variation.

Notably, none of the above studies demonstrating benefits of product heterogeneity from learning was executed in a manufacturing context using shop-floor-level product and process data. In manufacturing organizations, a significant amount of the knowledge acquired from learning is embedded in the organization—its processes, tools, and structures. Epple et al. (1996) and Levitt et al. (2013) provide evidence of this in their analyses of the introduction of second shifts at manufacturing plants. Both studies found almost complete knowledge transfer from the first to the second shifts when the second shifts began operation. The researchers concluded that the knowledge acquired on the first shift had been embedded in the organizations' tools and processes, which enabled the second shifts to achieve very quickly a level of productivity that it had taken the first shifts significant time to reach. Levitt et al. (2013) also investigated the effects of introducing new product variants and found that the addition of new variants hurt the learning rate for the initial variant.

The contrast of results about adding a second shift and adding new product variants is noteworthy. A second shift uses the tools and processes of the first shift. Because the products are the same on the two shifts, the tools and processes fit the product produced on the new shift. By contrast, the tools and processes developed for one product might not fit a different product. Under this condition, the tools can become a source of inertia that harms productivity.

Previous research in operations management and organizational behavior raises important questions regarding how the nature of product variety might influence organizational learning and knowledge transfer. We bring empirical evidence to the debate about whether product variety is harmful or helpful by examining the effects of different types of heterogeneity on organizational learning and the mechanisms through which these effects occur in a multiproduct manufacturing environment.

Products produced at high volumes provide both opportunities and motivation to learn. Where these high-volume products exhibit commonalities, there is potential to transfer knowledge acquired on one product to another. Thus, we expect knowledge transfer to occur across high-volume similar products, resulting in increased productivity in the short run and increased learning in the long run. By contrast, product variants that are produced at very low volumes provide limited opportunity or motivation for learning and, if there are few commonalities among those products or with high-volume products, limited scope for knowledge transfer. Moreover, such products can disrupt the flow of production of higher-volume products. Hence, such products can have a detrimental impact on short-run productivity and/or longer-run knowledge accumulation.

2.3. Definitions and Measures of Product Variety

Product variety can exist on many levels within a factory or firm, and studies within the production and operations management literature use many definitions of product variety. How product mix is defined and measured can affect its impact on productivity. Indeed, MacDuffie et al. (1996) found in a study of the automotive industry that different forms of product variety (e.g., model mix complexity, parts complexity, option content, option variability) had varied impacts on plant productivity. In the printed circuit board industry, Suarez et al. (1995) identified predictors of flexibility but did not find a relationship between flexibility and product cost or quality. In the case of the bicycle industry, Randall and Ulrich (2001) examined variation across attributes (e.g., material, geometry and size, color) of components and found that some variations increase production costs, whereas others instead impact "market mediation" costs (i.e., uncertainty in product demand). Finally, Kekre and Srinivasan (1990) examined product line breadth based on self-reported survey data from the Profit Impact of Marketing Strategy database in their analysis of more than 1,400 business units (most of which were part of a Fortune 500 firm) and found that firms with larger product lines have increased market share with minimal impact on production costs. Although these studies have advanced our understanding of the effects of product variety on various measures of plant performance, they have not examined the long-term implications of product variety for organizational learning and the development of a firm's knowledge stock. We address these fundamental issues by leveraging detailed plant-level data to analyze the effect of product variety on both productivity in the short run and learning in the long run.

3. Data and Methods

We analyze organizational learning and knowledge transfer within a firm that is a leading producer of high-technology hardware components and one of the leading revenue earners in its industry. The firm, which is U.S. owned, began moving production from the United States to a developing country in 2001, and by 2004, it had transferred all of the products to the production facility in the developing country. Our analysis draws on data from 2001 to 2011 at the manufacturing facility in the developing country. The setting we study has characteristics that make it exceptionally well suited to researching learning in a multiproduct environment: high-technology products that require sophisticated assembly and testing, multiple generations of focal products, large numbers of customized variations within generations, and a suite of market-related but physically quite different nonfocus products.

3.1. Data Collection

Our paper leverages three types of data: (1) quantitative archival data from the firm's production and human resource tracking systems, (2) surveys and semistructured interviews conducted with engineers and direct line worker trainers about process differences, and (3) participant observations at the facility. More details on the types of data collected on the site visits can be found in Table 1 in the online supplement. Over its history, the factory has kept detailed records of production volumes and yields, sales orders and shipments, labor hours worked, and employment histories. From this record, the data we obtained, spanning almost a decade, provide extraordinary detail, including order date and detailed specifications for each of millions of units produced. In addition, we obtained weekly data on labor inputs and detailed measures of process steps required for each product type as well as assessments by engineers and trainers of the relative complexity of these process steps. Our research also benefitted from knowledge obtained by extensive observation within the facility and from exceptional support and expertise of the company's management, engineers, and trainers.

3.1.1. Quantitative Archival Data. Details about each data type provided by the firm for this study are given in Table 1. We use the company's weekly shipment data from 2001 to 2011 as our measure of weekly firm output (q_t) and cumulative output, or production experience (Q_t). The sales and shipment tracking database, from which we retrieved these data, tracks details of all orders the factory receives and ships, and it includes data on these dates and order volumes.

Although shipment data can have limitations as a measure of output, because of a potential lag between completion of production and shipment to the customer, these limitations do not arise in our empirical context for several reasons. First, our shipment measure is shipment out of the production facility. The production facility does not hold inventory on-site. Shipment off the production site occurs as the next production step after products are completed on the line. Second, although the firm does not maintain regular records of off-the-line (e.g., preshipment) production volumes, we were able to gain access to a one-time estimate conducted by the firm (to the nearest thousand pieces) of off-the-line production volumes at an annual level from 2008 to 2013. These estimates match closely to our shipment measure. Third, because of distinctive specifications from customers, the firm produces almost entirely to order. Hence, inventory holdings are

Table 1. Overview of Quantitative Archival Data Sources

	Primary data			Secondary data	
Data source	Sales and shipment reports	Human resources employment database	Capital database	Production floor tracking system	Hard copies of weekly hours report
Data details	Volume of each order and date the order was placed and shipped	Date that each of the factory's over 20,000 employees was hired or resigned	Date that each piece of equipment was placed in service and the purchase price	Input and output production volumes for key testing steps	Weekly hours worked
Data availability	2001–2011	2001–2011	2001–2014	2004–2009	2004–2008
Calculated variable(s)	Shipment volumes (q_t, Q_t), product heterogeneity ($s_{n,t}$, G_t, M_t), order equivalents of product heterogeneity measures for instruments	Labor input (L_t)	Stock of capital in use (S_t)	Volume of products through key testing steps	Labor hours

minimal, and production–shipment lags are short. Furthermore, as long as any production–shipment lags vary randomly from week to week, these variations do not bias our estimates because such measurement error in a dependent variable does not bias coefficient estimates (Greene 2003), and the effects on the cumulative volume will be minimal because any week-to-week errors in production–shipment timing will offset each other when production is aggregated over time. Systematic variation in production–shipment lags could potentially cause bias, for example, if end-of-quarter reports incentivize shortening such lags as the end of quarter draws near. To investigate this possibility, we have included within-quarter variables denoting the number of weeks to the end of quarter. As we show, these variables do not affect our findings.

We use the company's weekly employed count of direct line workers from 2001 to 2011 as a measure of labor input (L_t). The employment database, from which we retrieve these data, tracks each employee's hire date, resignation date, and any promotions or changes in position at a daily level. Flexible local labor market conditions permitted the firm to adjust its workforce rapidly to accommodate changing demand. Hence, the count of employees and actual labor input track each other closely.[2] Moreover, as discussed further below, we find that the estimated coefficient on labor is virtually identical during periods of rising labor employment and during periods of declining employment.

We use the firm's internal record of capital equipment purchases, including the date each piece of equipment arrived at the facility and type and price of the equipment, to measure capital. According to the firm, new equipment would be placed on the line immediately after arriving at the facility. Although the types of capital purchases vary widely, from microscopes to alignment machines to heat cycle ovens, there are no large capital investments in single pieces of equipment that would be expected to take long periods to fully utilize. On the basis of our interviews and time at the facility, we know that testing equipment is the production bottleneck, because it processes only one to four parts at a time. To create a measure for capital that would accurately capture the production capacity, we crafted a capital construct that is a measure of the number of testers. This construct assumes that equipment utilization ramps up linearly from the time the equipment is purchased until the next tester is purchased. This measure allows older equipment to be fully utilized and new pieces of equipment to ramp-up to full utilization based on the time between equipment purchases (rather than a set time period). The results are virtually the same as those obtained when assuming that new testers are brought into use immediately.

3.1.2. Surveys/Structured Interviews. We worked with the firm's engineers to establish a list of process steps for each of the focus products. The aggregate of these lists encompassed 77 different processes across the focus products. Once the process list was defined, we distributed surveys to additional engineers, asking them to rank process difficulty by product; estimate the commonality of machinery, trainers, technicians, and engineers across focus products; and answer general questions about commonalities across products. These questions included eliciting the engineer's perceptions of what makes products similar and their experience with implementing new products on the line. The processes cover three stages of production: assembly, testing, and final preparation. Different engineers are responsible for each of these stages of production. Eleven engineers in the primary section of the factory filled out the survey from which we developed our engineering process measures. Two additional engineers filled out the survey for sections of the factory responsible for producing subcomponents. These 13 engineers together represented all of the production engineers for the focus products at the time we conducted the survey. A sample of the survey given to engineers can be found in the online supplement. We assessed interrater reliability of our respondents by calculating r_{wg}, which measures agreement among raters. Values of r_{wg} ranged from 0.75 to 0.96. All values were above 0.70, which indicates acceptable agreement (LeBreton and Senter 2008).

We also used a modified version of the process survey to conduct structured interviews with three trainers. The modified survey can be found in the online supplement. We talked through each process step with the trainer and asked for a process categorization and average training time for each process. We relied on our detailed interview with the head trainer for creating the training process measures used in our analysis.

3.1.3. Qualitative Data. Over the course of the three site visits, we spent a total of 19 days in the production facility, 12 hours observing the production floor, and an additional 2 hours actually participating on the production line (assisted by a trainer). We performed 41 semistructured interviews with managers, engineers, and trainers. These observations and interviews were transcribed, along with regular interactions with employees throughout the day, observations from a weekend outing spent with two employees, and interactions over the course of 24 meals shared with employees, into 112 typed pages of notes. All transcriptions were completed within at least 48 hours, the majority within 24 hours. Through these interactions, we gained insights to support our quantitative analysis including detailed knowledge of the history of the plant; variables measured and retained by management; how engineers and managers think about product similarity; and how production innovations, such as altered training procedures or new testing equipment, are incorporated into the flow of the plant.

3.2. Product Heterogeneity

Between 2001 and 2011, the facility manufactured 5 types of focus products and 14 types of nonfocus products, comprising 86% and 14%, respectively, of total production volume. Table 2 details for each of the focus and nonfocus product types: the shipment volumes as a percentage of cumulative shipped volume, number of distinct part numbers (a measure of variety within specific product types driven largely by customer-specific customizations), and physical volume relative to the primary focus product form factor.

As can be seen from Table 2, the focus products are similar in form factor (i.e., size and shape) and end use. Although the end use of focus products does not change across generations, technological advances result in changes of components within those products from one generation to the next and associated increase in capabilities. Each new generation of the focal product adds to the firm's product offerings; prior generations continue to be produced and sold. The firm considers these focal products its main priority and is a leader in this market. The flow of orders over time for the five generations of the firm's focus products is much less volatile than for the remaining products in the firm's portfolio. The focus products are expected to improve roughly every 6–18 months, and customers plan accordingly.

Table 2. Comparison of Focus and Nonfocus Products

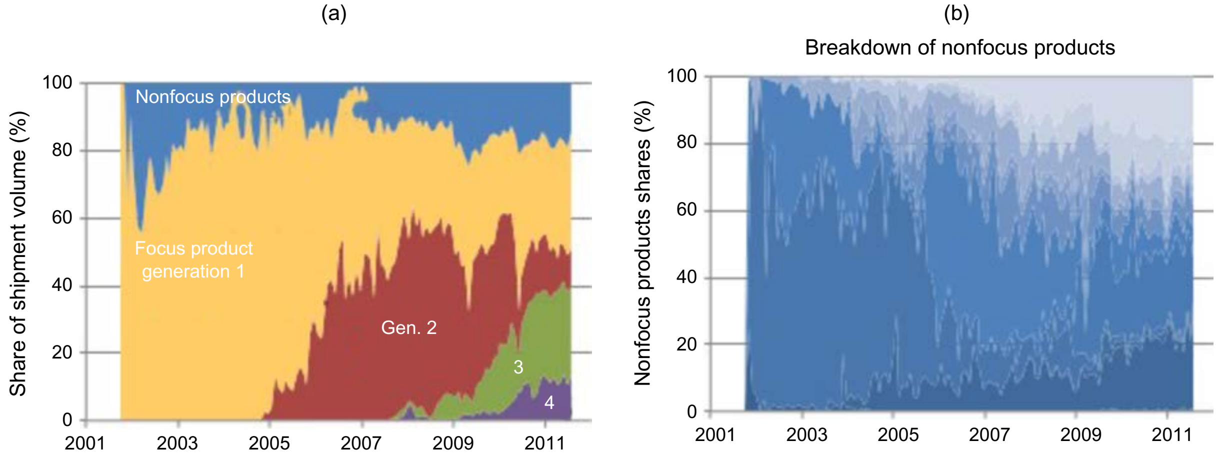
Focus or nonfocus products	Form factor	Percentage of cumulative shipped volume	Number of distinct part numbers	Physical size (volume) relative to focus FF1
Focus	FF1: Focus products 1–2	72.83	887	1.0
	FF2: Focus products 3–5	12.91	252	1.0
Nonfocus	Nonfocus product 1	3.16	2,227	1.0
	Nonfocus product 2	2.03	109	0.1
	Nonfocus product 3	1.95	127	1.2
	Nonfocus product 4	1.87	5	1.1
	Nonfocus product 5	1.79	385	3.1
	Nonfocus product 6	1.55	1,862	1.9
	Nonfocus product 7	0.73	51	6.7
	Nonfocus product 8	0.16	11	1.0
	Nonfocus product 9	0.11	14	8.2
	Nonfocus product 10	0.10	14	1.3
	Nonfocus product 11	0.05	157	9.0
	Nonfocus product 12	0.02	17	5.5
	Nonfocus product 13	0.01	25	0.5
	Miscellaneous	0.72	977	—

By contrast, the nonfocus products are a mixture of product types with different end uses for customers, different form factors based on industry standards, and different implementations of the underlying technology. We grouped the nonfocus products into 14 categories. The relative physical volume measure provides a sense of how different the various products are from each other. The physical size of the nonfocus products ranges from 0.1 to 9.0 times that of the physical size of the focus products. Although the underlying technology across all of the firm's products is based on the same scientific principles, the end products across these nonfocus groupings are dramatically different not only from the focus products but also from each other.

Figure 1(a) shows the shares of shipment volume over time for each of the focus product generations and the grouping of all nonfocus products.[3] Figure 1(b) shows the shares of nonfocus shipment volume over time for each type of nonfocus product. Each shaded region in Figure 1(b) is a unique nonfocus product grouping. As can be seen from the figure, the volume of each focus product is much greater than the volume of each nonfocus product.

Beyond core product differences, there is an additional level of variety within products as a result of customers requesting specific variations including tailored performance specifications, additional required

Figure 1. (a) Product Grouping Shares of Weekly Shipment Volume for Generations of the Focus Product and the Collection of Nonfocus Products and (b) Relative Shares of Nonfocus Product Types (Breakdown of the 14 Different Nonfocus Product Types as Shares of the Total Nonfocus Shipment Volume)



Note. Product share of generation 5 is too small to see with this plot.

tests, or cosmetic alterations (such as label placement). Each product, including each customization, receives a distinct part number. These customized parts can be produced in the facility over a period of time or can be one-time orders. The facility has manufactured 1,139 specific variations across the five types of focus products and 5,818 specific variations across the 14 types of nonfocus products as measured by unique part numbers, typically producing multiple units of each variation.

3.2.1. Measures. We utilize the data detailed above to create four measures of product heterogeneity—the share of nonfocus products, the generational overlap index (which captures the variety of product generations produced contemporaneously on the line), and customization indices for both focus and nonfocus products (based on the customer-specific product requests).

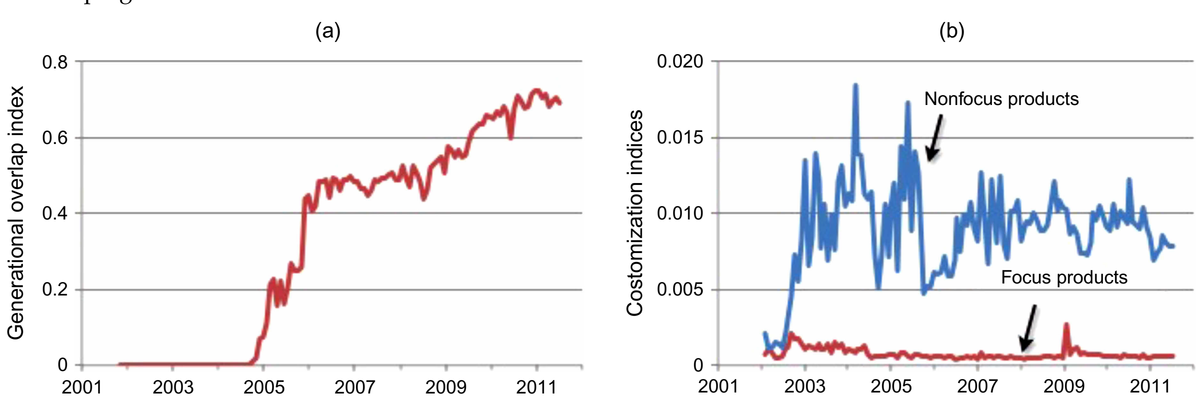
Using the shipment data, we calculate shipment volumes by product grouping and use these by-grouping data to calculate our heterogeneity measures. The share of nonfocus products is our first measure of product heterogeneity on the line. Figure 1(a) shows the share of nonfocus products over time.

Our second measure of product heterogeneity is a variant of the Herfindahl index that captures the mix of focus product generations being produced contemporaneously on the line. Two recent studies on the impact of product heterogeneity on productivity used the Herfindahl index to aggregate data across types of products or tasks into a single term representing the variety of products on the line (Wiersma 2007, Staats and Gino 2012). This index accounts for changes in product mix more broadly than would a measure of the share of one type of product. The Herfindahl index, or Herfindahl–Hirschman index, is the sum of squared shares, s, of the variable of interest:

$$H = \sum_{i=1}^{N} s_i^2. \tag{3}$$

Our index of coproduction of different generations of the focus products is one minus the Herfindahl

Figure 2. (a) Generational Overlap Index for Focus Products and (b) Customization Indices for Focus and Nonfocus Product Groupings



index of shares of those products. This definition facilitates interpretation because the index increases with increasing heterogeneity of products produced. We refer to this as our generational overlap index:

$$G = 1 - \sum_{i=1}^{5} s_i^2. \tag{4}$$

Importantly, this measure is based only on generations of focus products. Nonfocus products are very heterogeneous, motivating our inclusion of share nonfocus as our second heterogeneity measure. The degree of generational overlap is increasing in G; G takes on a value of 0 when only one generation is being produced. As the number of generations produced at a given time increases, the value of G rises; G also increases as the shares of different generations being produced become more equal. Figure 2(a) shows a plot of our generational overlap index.

Figure 2(a) shows the increasing generations of the focus product on the line over time. The increase in Garises because, as shown in Figure 1(a), the introduction of new generations does not result in the phasing out of previous generations.

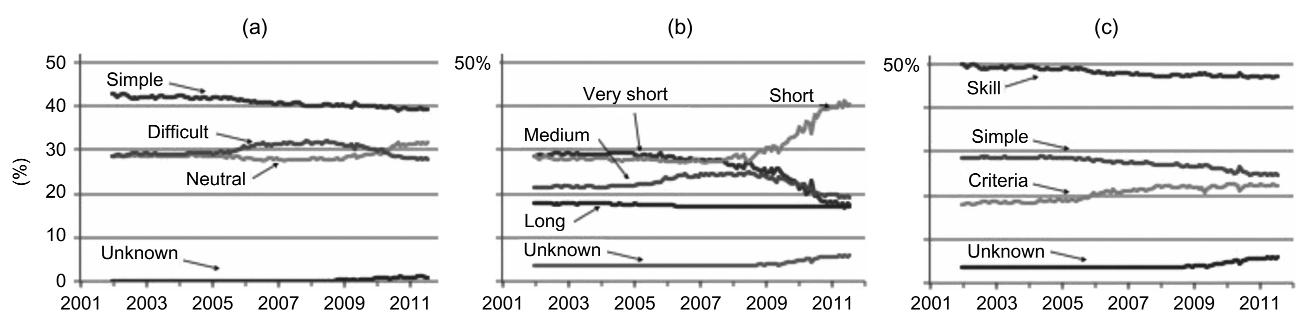
We define two measures—which we call our customization indices (M)—to capture product customizations within our focus and nonfocus product groupings undertaken by the firm to meet specific customer requests. These measures, for focus and nonfocus products, are total part numbers for each product category divided by the shipment volume of that product category. We denote these part-numbers-per-volume measures as $M_{f,t}$ and $M_{n,t}$. Figure 2(b) shows a plot comparing this measure for focus products and nonfocus products.

As can be seen in Figure 2(b), the ratio of part numbers to shipment volume is much higher for the nonfocus products than the focus products. Of course, the number of focus products produced is more than four times the number of nonfocus products. Hence, the total number of customizations of focus products is greater than the number of customizations of nonfocus products.

3.2.2. Variation in the Difficulty of Producing Different Products. Certain products may be more difficult to produce than others. To investigate this issue, we collected data on the process steps required for each generation of the focus products and three different measures of the difficulty of each of those steps: the category assigned to each process step in the firm's training system, the time required to teach new workers each of the process steps as part of their training system, and the difficulty (on a scale of one to five) assigned by engineers to each of the process steps. We collected data on all three of these measures in October 2011 through the surveys described in Section 3.1.2. To create weekly measures of the difficulty of the products being produced, we multiplied the process difficulty measure by the number of that type of process that went into the focus products shipped in a given week. For example, the company's training system has three categories for processes: simple processes, for which a machine conducts the primary action; skill-based processes, which require some training; and criteria-based processes, which require the direct line worker to meet particular criteria before passing the product on to the next process step. We have trainer categorization of all 77 process steps identified for the focus product generations, training time for each, and engineer difficulty rank for each.

Figure 3 shows overtime plots of (a) shares of levels of engineer difficulty ranking, (b) shares of levels of training times, and (c) shares of trainer categorization. The three metrics (engineering rank, training time, and trainer categorization) give a relatively consistent picture of the evolution of the difficulty of processes within the factory: as the focus products have evolved through their generations and become more technologically complex, the plant has shifted toward more criteria-based processes (which still have short, but not the very shortest, training times and which are perceived by engineers to be more difficult processes). At the same time, the more complex products require fewer engineer-ranked simple processes and fewer engineer-ranked difficult processes (with a rise in the number of processes the engineers rank as "neutral"), and fewer very-short-training-time processes.

Figure 3. Process Shares of (a) Engineering Rank, (b) Training Time, and (c) Training Categorization



3.3. Empirical Models

To analyze the organization's learning rate, we begin with the traditional learning model and expand this model to incorporate measures of product heterogeneity. We conclude by looking at transfer of knowledge across product generations (Epple et al. 1991, 1996; Benkard 2000).

3.3.1. Foundational Learning Model. We begin with a basic model of firm productivity that incorporates learning and labor input:

$$\ln(q_t) = \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_3 \ln(L_t) + \beta_4 \ln(S_t) + E_t, \quad (5)$$

where q_t is the production volume in week t as measured by products shipped, Q_t is the cumulative production volume through week t also as measured by products shipped, L_t is the labor input as measured by the total number of line workers employed in week t, S_t is the stock of capital-in-use in week t, and E_t is the error term. This functional approach is similar to the approach taken by Argote et al. (1990) and Epple et al. (1991, 1996).

To investigate whether the incremental gain from learning varies over time, we add a quadratic experience term, $\ln(Q_{t-1})^2$. To examine the impact of the mix of nonfocus versus focus products on the firm's overall productivity, we add the share of nonfocus products shipped in week t, $s_{n,t}$. To analyze the impact of the mix of generations of focus products on the line on the firm's overall productivity, we include our focus product generational overlap index, G_t, as defined previously in Section 3.2.1. To capture the impact of buyer-requested customizations on the firm's overall productivity, we include our two customization indices, part numbers per unit for focus products, $M_{f,t}$, and part numbers per unit for nonfocus products, $M_{n,t}$, as defined previously in Section 3.2.1:

$$\begin{aligned}\ln(q_t) = {} & \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_2 \ln(Q_{t-1})^2 + \beta_3 \ln(L_t) \\ & + \beta_4 \ln(S_t) + \beta_5 s_{n,t} + \beta_6 G_t + \beta_7 M_{f,t} \\ & + \beta_8 M_{n,t} + E_t. \end{aligned} \quad (6)$$

Many multiproduct environments, including ours, are intrinsically joint product environments; it is not possible, in principle, to determine how much labor is allocated to different product units or product generations, or how much capital. For example, at a given moment of time, a given worker may monitor an ongoing test on a unit of product from one generation while simultaneously preparing a product from another generation for testing. At the midpoint of our sample, the facility had approximately 2,500 workers producing approximately 200,000 units per week across two different product generations. By the end of our sample, roughly 4,000 workers were producing on the order of 350,000 units per week across five different product generations. These numbers underline the impracticality of allocating workers' time across product units. Hence, it is not possible to conduct estimation by using as dependent variables output per unit of labor for different product generations. A significant part of our work on this problem has entailed grappling with this joint-product challenge. We evolved a strategy of using total weekly units of output as the dependent variable and total labor and capital as independent variables while then utilizing product heterogeneity and customization measures to account for the variation in product mix over time. Extraordinary cooperation by management in responding to multiple data requests over time enabled us to form a large database from which we were able to examine product variety and, ultimately, define and calculate the heterogeneity and customization measures used in our model.

3.3.2. Learning Model with Cross-Product Knowledge Transfer. We next incorporate knowledge transfer into the model detailed in Section 3.3.1. We generalize the knowledge variable to permit differences in transfer of knowledge across products. This model is similar to the transfer model introduced by Epple et al. (1991) and further developed by Epple et al. (1996). The model is

$$\begin{aligned} \ln(q_t) &= \beta_0 + \beta_1 \ln(K_{t-1}) + \beta_3 \ln(L_t) + \beta_4 \ln(S_t) \\ &\quad + \beta_5 s_{n,t} + \beta_6 G_t + \beta_7 M_{f,t} + \beta_8 M_{n,t} + E_t, \\ \text{where} \quad K_t &= \sum_i s_{i,t} K_{i,t}, \\ K_{i,t} &= Q_{i,t} + \gamma(Q_t - Q_{i,t}), \\ s_{i,t} &= \frac{q_{i,t}}{q_t}. \end{aligned} \quad (7)$$

In defining knowledge when there are differences in cross-product transfer, we find it necessary to adopt a specification of the way in which knowledge about production of individual products aggregates to overall knowledge employed in production. As we discussed above, in a joint-product environment, it is inherent that there is not a separate productivity measure for each product. Hence, inference about transfer across products must be made from information about overall productivity of the suite of products produced in each period. Our specification of the knowledge variable, K_t, in Equation (7) weights knowledge specific to product i, $K_{i,t}$, by share of the product produced at date t, $s_{i,t}$. The weighing of $K_{i,t}$ by product shares to form K_t is based on the logic that knowledge about product i used in production is proportional to the share of product i being produced. This share-weighting formulation is, we believe, the most natural specification, but it is nonetheless an important assumption underlying our analysis of transfer. This model permits each product to accumulate knowledge from its own past production, $Q_{i,t}$, and to benefit from possible transfer of knowledge from other products ($Q_t - Q_{i,t}$). The parameter γ measures the proportion of knowledge gained from production of other products that is transferred to enhance knowledge for production of product i. Our previous model in Equation (6) implicitly sets γ equal to 1.

The transfer specification above assumes symmetry in transfer of knowledge across products, i.e., γ is the same for all products. We extend this model of knowledge accumulation to allow potential asymmetries in knowledge transfer across products.

We explore whether there is differential transfer of knowledge by introducing four transfer parameters that capture transfer from nonfocus products to focus products (γ_{n2f}), transfer from focus products to nonfocus products (γ_{f2n}), transfer "up" the generational hierarchy (from older focus products to newer products) (γ_u), and transfer "down" the generational hierarchy (from newer focus products to older focus products) (γ_d). This yields the following specification of knowledge accumulation for our six products:

$$\begin{aligned} K_{1,t} &= Q_{1,t} + \gamma_d(Q_{2,t} + Q_{3,t}) + \gamma_{n2f} Q_{n,t}, \\ K_{2,t} &= Q_{2,t} + \gamma_u(Q_{1,t}) + \gamma_d(Q_{3,t}) + \gamma_{n2f} Q_{n,t}, \\ K_{3,t} &= Q_{3,t} + \gamma_u(Q_{1,t} + Q_{2,t}) + \gamma_{n2f} Q_{n,t}, \\ K_{n,t} &= Q_{n,t} + \gamma_{f2n}(Q_{1,t} + Q_{2,t} + Q_{3,t}), \end{aligned} \tag{8}$$

where K_1–K_3 are knowledge stocks for our focus product generations, and K_n is the knowledge stock for our nonfocus products. We aggregate generations 3–5 of the focus product into one generation to avoid proliferation of parameters. As is evident from Figure 1(a), generations 3 and 4 were introduced at approximately the same time. These generations, as well as generation 5, share common technological advances that distinguish them from both the first- and second-generation products. Production of generation 5 was exceedingly small during the time frame of our data. Thus, K_1 is knowledge for generation 1, K_2 is knowledge for generation 2, and K_3 is knowledge for generations 3–5.

4. Results

We first present results from the model in Equation (6), which assumes that each product benefits equally from all prior units of all products produced. We then follow with results for the generalization in Section 3.3.2 that allows differential knowledge transfer across products.

4.1. Organizational Learning

4.1.1. Primary Findings. We report and discuss results obtained when estimating our models by ordinary least squares, in anticipation of our later finding that our results are robust to instrumenting for the potential endogeneity of labor and our product heterogeneity variables. All models reported in this paper are estimated with weekly data.

The models in Table 3 generally show significant learning by doing as well as significant coefficients for labor input and an insignificant coefficient on the measure of capital described previously. Although the coefficient on labor is not significant in column (1), it is in all subsequent models. The model in column (2) incorporates a quadratic in cumulative past production to investigate possible diminution in the effect of learning as experience accumulates. The significant negative coefficient on this term suggests that the rate of learning diminishes as cumulative production increases.[4]

In column (3), we add the share of nonfocus products, $s_{n,t}$, and the generational overlap index for focus products, G_t. We find that a higher proportion of nonfocus products decreases productivity. As we detailed in Section 3.2, these products differ in many important respects from the focus products. By contrast, increasing generational overlap in production increases productivity. Our finding that this form of product heterogeneity increases productivity is striking. In column (4), we introduce measures of customizations arising from buyer-specific requests for product modifications, with separate customization indices for focus and nonfocus products. We find that increases in customizations per unit of both product types reduce productivity. This finding about the difficulty of producing many variations of core products is in line with our qualitative findings from interviews with engineers. Specifically, one engineer stated, "Things are ... customized because we try to keep market share. The mix on the line of multiple shells and types of enclosures is hard."

To interpret the customization coefficients, it is useful to convert them to elasticities—the percentage change in production from a 1% change in customization, holding other variables constant. With the dependent variable expressed in logarithmic form, the elasticity of output with respect to any nonlogged independent variable, x, is $E_{q,x} = \beta_x \bar{x}$. We find that focus products have a customization index elasticity of −0.20; a 1% increase in customizations reduces production by 0.2%. Our nonfocus products have a customization index elasticity of −0.07. These elasticities show that a 1% increase in custom part numbers per unit volume of focus products has an adverse effect on productivity that is three times as large as a 1% increase in custom part numbers per unit volume of a nonfocus product. Interestingly, the coefficient of the share of nonfocus products becomes smaller and less significant in column (4), suggesting that the customizations (part numbers per volume) account for part of the negative effect of the share of nonfocus products. The effect of generational overlap remains positive and significant when the customization variables are included.

Table 3. Estimation Results: Learning Model

	(1)	(2)	(3)	(4)	(5)	(6)
β_1, *experience*	0.644***	3.789***	2.740***	0.421	0.242**	0.238**
$\ln(Q_{t-1})$	(0.192)	(0.446)	(0.408)	(0.323)	(0.102)	(0.101)
β_2, *experience sq.*		−0.103***	−0.080***	−0.006		
$(\ln(Q_{t-1}))^2$		(0.015)	(0.013)	(0.010)		
β_3, *labor*	0.220	0.561***	0.455***	0.264***	0.251***	0.268***
$\ln(L_t)$	(0.183)	(0.187)	(0.155)	(0.071)	(0.071)	(0.074)
β_4, *capital*	−0.133	0.011	0.197	0.065	0.052	0.058
$\ln(S_t)$	(0.232)	(0.147)	(0.124)	(0.096)	(0.099)	(0.099)
β_5, *share nonfocus*			−1.992***	−0.603	−0.658	−0.625
$s_{n,t}$			(0.335)	(0.411)	(0.402)	(0.396)
β_6, *generational overlap*			0.882***	0.533***	0.498***	0.519***
$G_{f,t}$			(0.248)	(0.144)	(0.142)	(0.141)
β_7, *customization: focus*				−806.896***	−810.703***	−807.936***
$M_{f,t}$				(85.504)	(85.314)	(85.691)
β_8, *customization: nonfocus*				−23.369***	−23.877***	−23.702***
$M_{n,t}$				(4.971)	(4.934)	(4.853)
Engineer difficulty rank avg.						−0.536
						(1.000)
Observations	461	461	461	461	461	461
R^2	0.835	0.860	0.880	0.956	0.956	0.956
Durbin–Watson	1.544	1.817	1.958	1.876	1.875	1.875
Log likelihood	−157.896	−120.276	−84.012	145.152	144.875	145.044

Notes. Newey–West robust standard errors are reported in parentheses. The constant term is omitted for firm confidentiality.
**Statistically significant at the 5% level; ***statistically significant at the 1% level.

Once we control for buyer-specific product modifications, as we do in columns (4) and (5), we no longer find evidence of a diminution in the rate of learning (the quadratic term in cumulative output becomes small in magnitude and statistically insignificant). This finding demonstrates the importance the kind of rich product detail that we have been fortunate to obtain for this analysis can play in understanding the dynamics of learning in a multiproduct facility.

Our ability to characterize three different types of product heterogeneity also offers an opportunity to reconcile past results from research on organizational learning with other results from operations management. Our finding with respect to the negative impact of buyer-specific product customizations echoes findings in the operations management literature that product changes are costly. Our finding with respect to the benefits of producing overlapping generations of focus products echoes prior findings in the learning literature about the potential benefits to productivity of product variety.[5] Thus, producing different generations of the same product helps productivity, whereas product customizations harm productivity. We examine in a subsequent section whether the positive effect of coproducing different generations of focus products is explained by knowledge transfer.

In column (6) in Table 3, we add the engineering difficulty measure. This measure has the anticipated algebraic sign showing that an increase in engineering difficulty decreases productivity. This variable, however, is not statistically significant, and including it does not affect our other coefficients. Hence, column (5) is our preferred model from our analysis thus far.[6] Note that the coefficient of capital has a positive sign in column (5) but is not significant, nor is capital significant in other specifications in Table 3. We explore the role of capital further in robustness analysis below.

It is useful to interpret the quantitative magnitudes of the estimates in column (5). The coefficients of the logarithm of experience, the logarithm of labor, and the logarithm of capital are elasticities. Hence, a 1% increase in experience increases output by 0.24%, holding all else constant. A 1% increase in labor increases output 0.25%, holding all else constant. A 1% increase in capital increases output by 0.05%, holding all else constant. The elasticity of output with respect to share nonfocus is −0.08. The elasticity of output with respect to the generational overlap index is 0.93. This is a strikingly large effect. As Figure 2(a) shows, the generational overlap index increased from 0 to 0.5 from 2005 to 2006. This coupled with the coefficient on 0.50 in column (5) implies an increase in production of 28% from the increase in generational overlap during that period. The index continues to rise in subsequent years to 0.75. Hence, over the period of our data, the generational overlap index is associated with a total increase in productivity of 45%. We explore these and other managerial implications in greater detail in Section 5.

The sum of the coefficients of labor and capital is well below 1 in all columns of Table 3, indicating that the firm experienced diseconomies of scale. Further investigation supports the robustness of the finding. When squared values of the logarithms of labor and capital are added individually or together, their coefficients are small and insignificant. The same is true when an interaction of the logarithms of labor and capital is included.[7] Other things the same, scale diseconomies would argue for dividing production among more than one production facility. Our results suggest, however, that other things would likely not be the same. Our estimates in Table 3 reveal that the firm accrues large benefits from learning by doing. Preserving those benefits would require transfer of knowledge across multiple facilities. Knowledge transfer is challenging: in another manufacturing context, Epple et al. (1996) found that learning after introduction of two-shift operation in a plant was roughly half the rate of learning from one-shift operation, which highlights the challenges in transferring knowledge, even within a given facility. A further challenge from multiple-facility operation would be preserving the benefits of coproduction of multiple product generations. Preserving the benefits of learning and synergies of coproduction likely contributes to the firm's decision to produce in a single facility.

4.1.2. Endogeneity and Robustness. One might be concerned about endogeneity in our product mix variables if the firm intentionally alters its product mix in a given week to improve productivity. We investigated potential endogeneity using instrumental variables. Order arrivals provide ideal variables for constructing instruments. Order placement is driven by customer demand, and the firm does not restrict the number of orders accepted by its sales staff. Thus, order flow is exogenous to our production facility.

We investigated potential endogeneity of all independent variables in column (5) of Table 3 except lagged cumulative output and capital. The intuition for treating capital as exogenous is the lead time needed to purchase the equipment in our firm's facility. As a result of this lead time, the plant management cannot adjust capital available in a given week to respond to random shocks during that week. We created instruments for the remaining variables as follows. We calculated for each week the share of nonfocus products in orders, a generational overlap index from orders, and customization indices from orders. We then calculated six-week averages of each of these variables and used the one-period lag of each these as instruments. As an instrument for the logarithm of labor, we used the lagged logarithm of labor. These are strong instruments. The first-stage F-statistics were 24 or higher for each of the five potentially endogenous regressors. Using these instruments, we tested for exogeneity of the five potentially endogenous variables and found p-values above 0.4 for all variables except *share nonfocus*, for which we obtained a p-value of 0.06. Thus, we find no evidence to reject exogeneity of any right-hand-side variable except *share nonfocus*, for which, as noted above, the share nonfocus in orders provides an appealing instrument.

In Table 4, we report instrumental variable estimates. For ease of comparison, column (5) of Table 3 is repeated as column (1) of Table 4. In column (2), we report the results of instrumental variable (IV) estimation treating all but lagged cumulative output and capital as endogenous and using the five instruments described in the preceding paragraph. In column (3), we report results of instrumenting only for share nonfocus products using the lagged six-week average of share nonfocus orders as described in the preceding paragraph. In column (2), the estimate of the coefficient of *share nonfocus* increases substantially relative to column (1) but is no longer marginally statistically significant. In column (3), the estimate of *share nonfocus* is much higher and is statistically significant. The change in the coefficient of *share nonfocus* with IV estimation is intuitive. A manager might choose to increase the share of the more-difficult-to-produce nonfocus products during weeks when the production process is going quite well (i.e., $E_t > 0$). By thus increasing $s_{n,t}$ during weeks of high E_t, the manager creates a positive correlation between the $s_{n,t}$ and E_t. This imparts an upward bias to the coefficient of $s_{n,t}$ when the equation is estimated by least squares. IV estimation removes

Table 4. Estimation Results: Instrumented Learning Model

	(1)	(2)	(3)
β_1, *experience*	0.242**	0.240**	0.216**
$\ln(Q_{t-1})$	(0.101)	(0.118)	(0.102)
β_3, *labor*	0.251***	0.285***	0.282***
$\ln(L_t)$	(0.071)	(0.078)	(0.070)
β_4, *capital*	0.052	0.088	0.138
$\ln(S_t)$	(0.099)	(0.116)	(0.107)
β_5, *share nonfocus*	−0.658*	−1.786	−2.450***
$s_{n,t}$	(0.395)	(1.157)	(0.802)
β_6, *generational overlap*	0.498***	0.432*	0.458***
$G_{f,t}$	(0.139)	(0.254)	(0.143)
β_7, *customization: focus*	−810.703***	−691.288**	−585.885***
$M_{f,t}$	(84.638)	(224.274)	(123.898)
β_8, *customization: nonfocus*	−23.877***	−30.305**	−39.668***
$M_{n,t}$	(4.831)	(13.277)	(8.197)
Observations	461	461	461
R^2	0.956	0.954	0.951
Durbin–Watson	1.875	1.934	1.950

Notes. White standard errors are used and are reported in parentheses. The constant term is omitted for firm confidentiality.

*Statistically significant at the 10% level; **statistically significant at the 5% level; ***statistically significant at the 1% level.

this upward bias and, hence, yields a larger estimate of the cost of increasing the share of nonfocus products.

Although correcting for endogeneity of $s_{n,t}$ impacts the coefficient magnitudes and significance levels to some degree, the correction does not change our substantive findings. Interestingly, the coefficient of capital increases substantially in magnitude and, although falling short of conventional levels of significance, becomes somewhat more significant with a p-value of 0.2 in column (3). Overall, then, the IV estimates support our findings and conclusions with respect to learning in a multiproduct environment.

In addition to correcting for endogeneity, we undertook several additional robustness checks. First, we investigated robustness of our generational overlap measure by reducing the exponent to a level of 1.5, $G = 1 - \sum_{i=1}^{5}(q_{it}/q_t)^{1.5}$, from the baseline value of 2, $G = 1 - \sum_{i=1}^{5}(q_{it}/q_t)^2$. This allows the generational overlap index to give larger weight to product generations with smaller shares. Our results are robust to this alternative calculation of the generational overlap index.[8] We verified the robustness of our results to adding controls for differences in process difficulty across our generations of focus products.

Second, we investigated multiple alternative measures of capital: (i) the cumulative expenditures on testers instead of the cumulative number of testers to weight the equipment by price; (ii) the cumulative number of all pieces of equipment (not just testers) and (in a separate run) cumulative expenditures on all pieces of equipment to see whether using all equipment is a better measure of the relationship between capital and productivity than just the type of equipment that is the productivity bottleneck; and (iii) the cumulative number, the cumulative expenditures, and the ramp-up measure detailed in Section 3.1.1 of the top three categories of equipment as determined by total purchase price. These three categories of equipment are testers (40% of total equipment costs), alignment machines (10% of total equipment costs), and scopes (9% of total equipment costs). In addition to being the largest contributors to overall capital costs, according to our interviews, these three categories are also the types of equipment that are most influential in determining yields and thereby productivity in the facility. With each of these measures, we found the core of results of our model to remain the same and the coefficient on the capital measure to be insignificant. Hence, our results are robust to all of these alternative ways of including capital in our model.

A reviewer made the quite plausible suggestion that the firm might have initially had more capital than required for production, which could potentially account for a lack of significance of capital. The firm made substantial early purchases of capital and then made no substantial additional purchases during the first six months of our sample. Thus, as the reviewer conjectured, the firm appears to have had excess capital during the initial period of our sample. In light of this, we reestimated our model allowing the coefficient of the logarithm of capital to be different for the period of no new tester purchases from the coefficient for the period after new tester purchases began. The difference in coefficients between these two periods was small (0.009) and not significant ($p = 0.60$). Thus, although promising, this explanation does not account for the insignificant estimate of the effect of capital.

Although it is reassuring that our core findings are robust to inclusion of alternative measures of capital, the somewhat insignificant estimated effect of capital is puzzling. The lack of significance of capital might be explained by a distinctive feature of this production environment. Capital appears to be used in approximately fixed proportions to output.[9] In the extreme, if the fixed-proportions hypothesis were exactly correct, a regression of capital on outputs would fit perfectly. In practice, however, the firm might keep excess capital to permit preventive maintenance and to hedge against machine breakdowns. With some surplus capital in place, production might not exhibit systematic short-run response to variation in capital. Moreover, even if the minimum required capital is proportional to the number of units produced, there may be some scope for capital-labor substitution because more than the minimal amount of capital could avoid bottleneck situations, such as workers waiting to access a relevant piece of equipment. As capital utilization increases, the potential for capital to constrain output increases, which suggests that periods immediately before arrival of a new piece of equipment might exhibit lower than average productivity. We investigated this conjecture by including an indicator variable equal to 1 for observations one, two, or three weeks prior to the arrival of a new piece of capital. This indicator variable has a negative coefficient, whereas other coefficients are very little affected by inclusion of the indicator variable. The estimated coefficient of the indicator variable is equal to −0.056 and is highly significant, which implies that productivity is 5.6% lower than "normal" in the periods immediately preceding the arrival of a new piece of equipment. As an alternative approach to the same idea, we included the week-to-week change in the ratio of capital to labor. This coefficient is positive (2.59) and approaches significance ($p = 0.13$). Hence, these two approaches tell a similar story about the benefits additions to capital. Although this evidence is far from conclusive, it demonstrates that our findings are consistent with an important role for capital while also providing further evidence of robustness of our findings to alternative framings of the role of capital.

Third, we investigated alternative measures of labor. Our measure of labor is the number of workers rather than hours worked. Because our measure does not capture overtime hours, our estimates may not fully capture the effects of labor. Use of overtime is more likely during times when the number of workers is growing rather than when the number of workers is declining. Hence, if our estimates were impacted by overtime, we would expect a different coefficient on labor during times when the number of workers is increasing from when it is decreasing. We allowed the coefficient of labor to differ depending on whether the amount of labor was increasing or decreasing. The estimated difference was negligible in magnitude (0.001) and not significant ($p = 0.95$), which provides encouraging evidence for the validity of our labor measure.

Fourth, we investigated whether the residuals exhibit serial correlation in our preferred model in column (5). Estimating with a first-order autoregressive error, we find a small (−0.006) and insignificant coefficient ($p = 0.89$). The estimated autocorrelation function and associated Q-statistics show no evidence of serial correlation up through 12 lags but significant correlation at the 13th lag. An effect at the 13th lag could potentially arise, for example, if the facility exerts some extra effort at the end of the quarter to speed shipment of completed products to meet delivery requests. Estimating the model in column (5) with an autoregressive term at the 13th lag, we obtain a significant but modest autoregressive coefficient of 0.27. The coefficients and significance levels of the variables in column (5) were otherwise not notably affected aside from an increase in the significance of share nonfocus. Hence, there is little serial correlation and no effect on our conclusions when we account for the modest serial correlation evident at quarterly frequency.

Fifth, we extended the model to investigate whether knowledge depreciates. Following Argote et al. (1990), we replaced cumulative production, Q, with a measure, K, that allows for potential depreciation: $K_t = \lambda K_{t-1} + q_t$. If knowledge depreciates, $\lambda < 1$. If there is no depreciation of knowledge, $\lambda = 1$. When we estimated the depreciation parameter we found that it was not significantly different from 1, and we therefore concluded that the facility does not exhibit knowledge depreciation.

Sixth, we investigated the potential for confounding learning and time-varying influences unrelated to learning. To do this, we added a time trend to the model in column (5) of Table 4. We find the estimated coefficient of the time trend to be quantitatively small and statistically insignificant. The statistical significance of all other variables is unchanged by the inclusion of the time trend.

4.2. Knowledge Transfer

A key and robust finding from our analysis thus far is that simultaneous production of overlapping product generations enhances productivity. This is conceptually distinct from the impact of multiple generations on knowledge acquisition and transfer. We now extend our model to investigate transfer in more detail. The framework in Equation (9) is a generalization of the framework we have studied thus far and reduces to the latter when all of the transfer parameters equal 1. We estimate this model by nonlinear least squares.[10]

Column (1) of Table 5 reports the results of estimating the model in Equation (9). The coefficients of the knowledge variable (K_{t-1}), labor input (L_t), capital (S_t), and each of the product heterogeneity terms ($s_{n,t}, G_t, M_{f,t}$, and $M_{n,t}$) retain similar magnitudes and significance levels as their counterparts in column (5) of Table 3. This similarity speaks to the robustness of our findings.

Turning to the estimates of the transfer parameters, we see, as expected, that transfer from older to newer focus products, γ_u, is positive and statistically significant. The parameters capturing transfer between focus and nonfocus products, γ_{n2f} and γ_{f2n}, are insignificantly different from 0 (and setting them equal to 0, as

Table 5. Estimation Results: Knowledge Transfer Model

	(1)	(2)	(3)
β_1, *knowledge*	0.266***	0.256***	0.273***
$\ln(K_{t-1})$	(0.074)	(0.045)	(0.047)
β_3, *labor*	0.214**	0.232***	0.182*
$\ln(L_t)$	(0.085)	(0.081)	(0.096)
β_4, *capital*	0.047	0.045	0.039
$\ln(S_t)$	(0.064)	(0.061)	(0.060)
β_5, *share nonfocus*	−0.283	−0.339*	−0.380*
$S_{n,t}$	(0.198)	(0.201)	(0.202)
β_6, *generational overlap*	0.616***	0.591***	0.556***
$G_{f,t}$	(0.181)	(0.170)	(0.175)
β_7, *customization: focus*	−815.014***	−817.215***	−815.067***
$PPV_{f,t}$	(24.661)	(25.129)	(24.934)
β_8, *customization: nonfocus*	−21.232***	−21.326***	−22.064***
$PPV_{n,t}$	(2.488)	(2.518)	(2.553)
Transfer: newer → older focus	−2.493***	−2.426***	−2.235***
γ_d	(0.748)	(0.707)	(0.518)
Transfer: older → newer focus	1.243**	1.343**	
γ_u	(0.534)	(0.571)	
Transfer: nonfocus → focus	0.162	0	0
γ_{n2f}	(1.930)		
Transfer: focus → nonfocus	−0.133	0	0
γ_{f2n}	(0.481)		
Transfer: gen 1 to gen 2			1.770**
			(0.903)
Transfer: gens 1–2 to gens 3–5			1.423**
			(0.594)
Observations	461	461	461
Log likelihood	154.408	154.249	154.637

Notes. Standard errors are reported in parentheses. The constant term is omitted for firm confidentiality.

*Statistically significant at the 10% level; **statistically significant at the 5% level; ***statistically significant at the 1% level.

in column (2) of Table 5, does not change the results). By contrast, the coefficient measuring transfer from newer to older products, γ_d, is negative and statistically insignificant.[11] As we noted earlier, the introduction of newer products might entail changes in tooling and processes that adversely affect production of older products. Although the magnitude and significance of the estimate in column (1) surprised us, the results match insights we gained from our discussions with the firm. One high-level manager stated, "In general, we focus our energy for making process improvements on newer generations of products. This makes our engineering investments more effective and requires less customer notification/qualification." This explanation corroborates that improvements on newer products can negatively impact the production of older products. It is important to emphasize, however, that knowledge from learning by doing continues to increase for the older focus products. Although there is negative transfer from new to old products, this is more than offset by the knowledge the firm acquires via continued production of older products. Put differently, production of new products reduces the amount learned from production of older products, but it does not entirely offset knowledge gained from continued production of older products. More formally, in the following equation for knowledge acquired for the first product, $K_{1,t} = Q_{1,t} + \gamma_d(Q_{2,t} + Q_{3,t}) + \gamma_{n2f} Q_{n,t}$, the first term on the right-hand side is greater than the second term throughout the course of our sample; i.e., $Q_{1,t} > \gamma_d(Q_{2,t} + Q_{3,t})$. Hence, $K_{1,t}$ continues to increase despite the negative transfer to product 1 from newer products 2 and 3. The same applies for product 2; the negative transfer from product 3 is less than the knowledge acquired via continued production of product 2.

We next separate the forward transfer parameters to allow transfer from the first generation to the second to differ depending on whether the knowledge is transferring from generation 1 to generation 2 or from generations 1 and 2 to generations 3, 4, and 5 (see column (3) in Table 5). Although the magnitude of the transfer coefficient from generation 1 to generation 2 is slightly larger than that when transferring knowledge from generations 1 and 2 to generations 3, 4, and 5, the difference is not significant. The estimated values of the forward transfer parameters, although significantly different from 0, are not significantly different from 1. Hence, we do not reject the hypothesis that knowledge acquired per cumulative unit of a new product i is the same as the knowledge transfer per unit from older products.

In looking across the models in Table 5, we see a very modest decline in the coefficient of the generational overlap index. This modest change highlights the distinction between the generational overlap measure and knowledge transfer. The former captures synergies from coproduction of multiple generations in a given period. The latter captures effects on knowledge accumulation and retention. Estimates of the other (i.e., nontransfer) parameters of our model are similar across the three specifications in Table 5. Hence, this analysis of transfer reinforces the robustness of our primary findings with respect to the importance of learning by doing, share nonfocus, generational overlap, and customizations.

In further analysis (not shown), we added a time trend to the model of column (1) of Table 5 and also allowed for possible depreciation of knowledge. We find that the time trend differs negligibly from 0, and the depreciation parameter, λ, does not differ significantly from 1. Hence, there is no evidence of "forgetting" and no evidence of gains in productivity associated with time per se as distinct from gains arising from learning.

As we have seen, our estimates imply that the firm was successful in transferring knowledge forward to new product generations. How was this accomplished? Based on discussion with the managers of the firm, we learned that the firm developed and implemented innovations in production practices by leveraging experiences with early generations of products to enhance the efficiency of production of newer products. Innovations in testing practices are one example. Managers and engineers cite innovations in testing that emerged from knowledge gained during production, innovations that led to internal reconfiguration of testing equipment and procedures to allow quicker testing of focus products and more flexibility for use across different generations of products and across product customizations. The flexibility developed from these innovations in testing practices may have played a role in facilitating the transfer of knowledge across product generations. In addition to facilitating knowledge transfer, these innovations in testing practices may also have served to embed important acquired knowledge in the testing routines, thereby facilitating the retention of knowledge that we have found in our analysis.

As a second example of productivity-enhancing knowledge acquisition, the firm discovered that "block" changes, which entail implementing changes simultaneously as a group or "block," rather than implementing a series of individual changes at different points in time, enhanced efficiency. This new approach was first applied and discovered to enhance productivity during implementation of a set of product changes required for compliance with new environmental regulations (specifically, the European Union's Restriction on Hazardous Substances Directive). This strategy of block changes often involves changes to components or subassemblies across product generations or across different products. These changes may help explain the firm's efficient transfer of knowledge across products, as learning is embedded in machines, components, or other hardware changes common across multiple products. These changes may also have contributed to the significant positive impact of coproduction captured by our generational overlap index.

5. Managerial Implications

In addition to advancing the frontier in understanding organizational learning, quantification of learning in a multiproduct environment provides valuable information for managers. Findings with respect to learning provide guidance about circumstances in which synergies across products can be expected as well as those in which there might be no synergies or even adverse impacts of multiproduct production. Regarding the former, coproduction of overlapping generations of a given product family can give rise to significant synergies. Our investigation of transfer between focus and nonfocus products suggests that there is no synergy in learning across these two product families. Products in these two product families differ markedly from each other, and our results show that neither family benefits from knowledge acquired in producing the other. Extensive product variety, such as that arising from customizing individual products to meet buyer needs, can also lead to adverse effects on productivity. These findings suggest important considerations for firms in planning new production facilities, in deciding which production activities should be housed in a given facility, in setting policy about the extent of product variation that will be undertaken in response to buyer requests for customization, and in taking account of learning by doing in anticipating future labor requirements. These findings can also be useful to firms in determining price premia to set in order to make such customizations profitable.

Over the time frame of our analysis, the facility we study achieved more than a 16-fold increase in weekly production. It is instructive to provide an accounting of the role of various factors in enabling this increase. Our estimates in column (3) of Table 5 imply that a doubling of cumulative output permits increasing production by 21.6%, holding labor and other factors (product mix and product customization rates) constant. Cumulative output doubled approximately 6.2 times over the period that we study. Hence, learning permitted increasing production by a multiple of $(2^{6.2})^{0.216} = 2.5$, holding labor constant. The generational overlap index increased over the time period we studied from 0 to 0.75. Holding labor and other factors (customizations and cumulative volume) constant, our estimates in column (3) of Table 5 imply that the increase in generational overlap would have permitted an increase in output by a multiple of $e^{0.458 \cdot 0.75} = 1.41$. Labor input increased fivefold, contributing a multiple of $5^{0.282} = 1.57$. The number of testers increased 22-fold between the first six months and last six months, implying a $(22)^{0.138} = 1.53$ multiple.[12] Over the time period we study, customizations for focus products were reduced markedly. During the last six months of the period we study, focus customizations were 60% lower that during the first six months. Other things constant, this contributed a proportionate increase in output of $e^{585.9 \cdot (0.000593 - 0.00156)} = 1.76$ and provides a striking illustration of the magnitude of the productivity effects of providing buyer-specific product variants. Turning to nonfocus products, we find negligible difference in the six-month customization average at the end compared with the six-month average at the beginning of our sample period. Hence, other things constant, we find no effect of nonfocus customizations in accounting for the increased output at the end relative to the beginning of the period we study. The change in share nonfocus products was modestly lower during the last month of the production period relative to the first month, giving rise to only a 1.09 multiple to production evaluated with the share nonfocus coefficient from column (3) of Table 5.

Drawing together the above, we find that learning, increased production of overlapping product generations, increased labor, increased capital, reduction of focus product customizations, and reduction of share of nonfocus products yield a proportionate increase in output over the period we study of $(2.5 \cdot 1.41 \cdot 1.57 \cdot 1.53 \cdot 1.76 \cdot 1.09) = 16.2$. The factors included in our model thus account for the more than 16-fold increase in output achieved by the firm over the time period of our study.

Our production function estimates also permit answering "what-if" questions. For example, what would be saved by decreasing the proportion of focus product customizations by 1%? This can be answered by determining the amount by which labor would be able to be decreased (or saved) as a consequence of decreased customizations when holding constant the number of units produced. From Equation (6), we see that this requires holding constant the following: $\beta_3 \ln(L_t) + \beta_7 M_{f,t}$. Inserting our estimates from column (3) of Table 5, this implies holding constant $0.282 \ln(L_t) - 585.9 M_{f,t}$. Using this result and evaluating at sample averages, we find that a 1% decrease in customizations would allow decreasing labor inputs by approximately 1.5%. The same analysis for nonfocus products reveals that a 1% decrease in nonfocus customizations would enable approximately a 1.3% decrease (or savings) in labor. The firm would, of course, need to balance the cost savings associated with reduced labor requirements against potential revenue lost from reduced customer-specific product offerings.

6. Conclusion

The production and operations management literature generally emphasizes that producing a variety of products decreases productivity and focuses on developing strategies to counteract the complications of a varied product mix (Womack et al. 1990, Fisher and Ittner 1999, Desai et al. 2001, Suarez et al. 1995). By contrast, the organizational learning literature provides cases where organizations learn more from diverse than from homogeneous experiences and where product heterogeneity is beneficial for learning (Haunschild and Sullivan 2002, Schilling et al. 2003, Bernard et al. 2010, Wiersma 2007).

Drawing on 10 years of production and human resource tracking system data from a manufacturing facility that is a leading producer of high-technology hardware components, we demonstrate that whether product heterogeneity is helpful or harmful depends on the extent of the differences between the products on the line and the volume of products produced. Demonstrating the benefit of similarity for learning, we find that productivity improves when multiple generations of the same product are produced at the same time. We investigated a mechanism, knowledge transfer, which could explain the benefits of product heterogeneity. The positive impact on productivity of having multiple generations of the same product on the line is explained in part by the firm's ability to transfer knowledge from older to newer generations of the product. We also find that having multiple generations of the focus product on the line is beneficial to firm productivity above and beyond the benefits of generational knowledge transfer.

At the same time, we find productivity is decreased when the production line is faced with products that are very different (e.g., nonfocus products) and when the products are low volume, irrespective of how similar or different they are; that is, both focus and nonfocus customizations harmed productivity in the short run. Furthermore, experience on the nonfocus products does not transfer to the focus products (see Table 5). Thus, we find that the effect of product heterogeneity depends on both how similar products are and how frequently they are produced. Our results advance theory about when product heterogeneity is helpful and when it is harmful for productivity and learning.

In manufacturing organizations, a significant amount of the knowledge acquired from learning is embedded in materials, tools, and technology (including process and design decisions). When a new product variant shares common processes and design components, the learning that is acquired producing the previous generations of product can be captured in the materials, tools, and technologies made for the new product. If production volume for the new product generation is expected to be high, there are strong incentives to reconfigure the facility to match the needs of the new product and to embed the knowledge from the previous generation in the tooling and processes to benefit the next generation. Examples of this embedding of learning in materials, tools, and technology in our firm include "block changes" in design and process across products, modifications in plant layout, and updates in instruction procedures for direct line workers. This pattern of reconfiguring the plant for new products explains why we see positive transfer from older to newer generations of the product and negative transfer from newer to older generations.

When products are too different—such as the differences between our focus and nonfocus products—the materials, tools, and technologies (including process and design) developed for one product will not fit another. Coproducing such different products on the line will not help productivity and may even harm productivity, if the lack of fit is great. Furthermore, if the products are very different, knowledge would not transfer from one to another.

When low-volume customizations are allowed on either the focus or nonfocus products, the organization has few opportunities to learn and little incentive to change the materials, tooling, and processes to fit the customizations. Productivity benefits of task repetition by individual workers that occur when producing recurring products are diminished, as workers are forced to make minor adjustments with each new product that comes through. Thus, low-volume customizations—of either focus or nonfocus products—have a negative effect on productivity.

In addition to enabling us to provide a comprehensive analysis of learning and other factors influencing productivity, the rich data set that we collected provides us with strong instruments to investigate potential endogeneity. Our measures of product order arrivals provide ideal instruments for the product heterogeneity variables because such order arrivals are the central driver of heterogeneity of products produced, but the timing of order placements is exogenous to the production process at the firm. As we demonstrated, our findings are robust to correction for potential endogeneity bias.

We took an interdisciplinary approach to studying organizational learning drawing on insights from engineering, economics, organizational behavior, and operations management. We collected both quantitative and qualitative data, which allowed us to examine at a fine-grained level the nature of products in our multiproduct manufacturing facility. Our in-depth focus enabled us to shed light on the impact of different forms of product variety on organizational learning and thereby advance theory about learning.

Our study is, of course, limited to one firm. Although studying only one firm allows us to focus on a specific multiproduct context, gain a deep understanding of the organization, and collect a rich data set, it will be important to test the implications of product heterogeneity on learning and knowledge transfer in additional settings. We expect our results will most likely generalize to other facilities with labor-intensive production of complex products. Interesting additional contexts that would enable us to identify the boundary conditions for our findings include highly automated mechanical assembly factories as well as different industries, such as pharmaceuticals or chemicals (Lieberman 1984), where production focuses on processes rather than products.

Our findings have important implications for organizations that manage a multitude of products in one location. Our results suggest that industries that see products evolve through generations can benefit—in terms of productivity—from coproducing older products at the same time as newer ones in the same facility. On the other hand, producing distinctly different products and customizing products to meet different buyer specifications can hurt firm productivity. In addition to building understanding of the mechanisms of learning by doing, our approach can also aid firms in evaluating whether the revenue benefits of offering particular products and customer-specific customizations are sufficient to compensate for the adverse productivity effects of product variety offered.

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Endnotes

[1] In the case of Smith (1776), these benefits were through improved individual worker performance from task repetition, time saved not having to change tasks, and innovations in machines dedicated to individual tasks.

[2] Labor hours and employee count are correlated with $\rho = 0.88$ for the time period for which we have overlapping data. Our results are robust to the use of either labor input measure.

[3] To facilitate visual illustration of patterns over time, all figures show four-week averages of variables being portrayed.

[4] The peak of this quadratic function occurs well beyond the cumulative volume observed in our data. Hence, this specification implies that learning by doing continues throughout the entire production period that we observe.

[5] One notable exception is Benkard (2000), who finds that coproduction of two models has a negative effect on productivity.

[6] We see similar results when we add in our other two process difficulty measures, share of training categorization and average training time. In these cases as well, the measures themselves are not significant and have minimal change to the magnitudes and no change to the significance levels of the core variables in the model. This is reassuring in suggesting that our product heterogeneity measures are indeed capturing differences in difficulty of producing products as product mix changes.

[7] A referee noted—and we agree—that our estimated coefficient of labor is lower than typically found in facilities producing only one product or a small number of products. As further sensitivity analysis, we estimated our model forcing the coefficient of labor to be a relatively extreme value of 0.75, which is triple the estimate in column (1) of Table 4. Not surprisingly, this resulted in a reduction of the coefficient of learning. However, even with this tripling of the coefficient of labor, the magnitude of coefficient on learning remained large (0.15) and highly significant ($p < 0.001$). Although we have no reason to think our estimated labor coefficient is biased downward, this result is quite reassuring about the importance and robustness of learning in our setting.

[8] Concern has been raised about potential bias in the Herfindahl index, the basis for our generational overlap index, as a result of measurement error (Hall 2005). Bias can arise when the index is calculated from count data with a small number of counts. Our data do not suffer from this problem because our product counts are exceedingly large. For a discussion of the merits of the Herfindahl index relative to other indices, see Palan (2010).

[9] For example, a regression of number of testers against weekly production volumes for all product types explains 86% of the variance, whereas the corresponding regression for labor explains 61% of the variance. Although far from conclusive, these regressions provide some support for a close correspondence between capital and output.

[10] For our model, nonlinear least squares is also the maximum likelihood estimator.

[11] Benkard (2000) studies learning for two models with one symmetric parameter to capture spillovers from the first model to the second model, and vice versa. In a sensitivity test, Benkard (2000) relaxes the symmetric constraint, but the author finds no evidence that spillovers flow more from one model to the other. This is in contrast to our findings where spillovers occur from older generations to newer generations across multiple generations.

[12] This 22-fold increase in testers relative to the fivefold increase in labor is noteworthy. It is useful to bear in mind that because it is durable, capital is cumulative, whereas labor is weekly. By way of comparison, cumulative labor at the end of our sample was more than 30-fold higher than at the beginning of our sample.

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