Benefits of Bounded Diversity: Organizational Learning and Knowledge Transfer in a Multi-Product Manufacturing Environment

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Abstract

Organizational learning and knowledge transfer are key elements within any firm when considering the firm's competitive advantage and long-term goals. Yet, the roles of learning and knowledge transfer in a multi-product production setting are not well understood. Production and operations management literature suggests production of a variety of products is largely harmful, yet the organizational learning literature suggests there may be benefits to heterogeneity.

This work explores the significance of a multi-product environment on organizational learning and knowledge transfer by studying a US-owned overseas manufacturing facility that is a leading producer of high technology hardware components. The firm produces 5 generations of high-volume focus products as well as a collection of non-focus products [an assortment of small volume products related to the focus products].

We draw on 10 years of firm archival data and qualitative data collected to shed insights into how different levels of product mix (5 generations of a focus product, thousands of minor variations on products to meet customer specifications, and an assortment of small volume products related to the focus product) impact organizational learning differently and why knowledge transfers across some products and not others by examining the role that processes play in these product transitions.

Our results reconcile differences between the organizational learning and production and operations management literatures by finding support for both advantages and disadvantages to product mix on the production line depending on the extent of product differences. We find that short-term productivity improves with bounded diversity – specifically, 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 may in part be explained by the firm's ability to successfully transfer knowledge from older to newer generations of the product, improving long-term productivity, though we find benefits for focus product heterogeneity over and above the benefits from knowledge transfer. In contrast, we find short-term productivity is decreased when the production line is faced with variety across products that are too different from each other (e.g. different form factors) and across minor product variations (i.e. customer-specific product variations).

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Chapter 1

Introduction & Theoretical Motivation

An organization's ability to learn from its experience and to transfer this accumulated knowledge within its organizational boundaries can be a critical contributor to its competitive advantage. However, the roles of learning and knowledge transfer in today's increasingly common multi-product production settings are not well understood. This chapter first overviews organizational learning and knowledge transfer, and then moves to review the literature in both operations management and organizational science on the impact of product mix on productivity and learning, and concludes with a discussion on measures of product mix.

1.1 Organizational Learning

Learning curves have been found within many organizations and are indicative of how that organization is improving with experience [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 [Irwin and Klenow (1994), Benkard (2000), Argote et al. (1990), Epple et al. (1991)].

The classic form of this organizational learning curve is given as

$$y_i = aQ_i^{-b} \tag{1.1}$$

and is often written for estimation purposes in logarithmic form

$$\ln y_i = c - b \ln Q_i \tag{1.2}$$

where y is the unit cost or number of labor hours to produce the ith unit, 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 i, b is the learning rate, and i is a time subscript [Argote (1999)]. Other metrics such as defects per unit or accidents per unit have been shown to follow a learning curve pattern, thus y can represent different performance metrics that vary, and generally improve, with experience, i.e. the production of the Qth unit [Argote (1999)]. This standard organizational learning equation defines the learning rate b with a negative sign because the standard performance metrics, unit cost or labor hours per unit, decrease with experience and learning. Alternate performance metrics, such as yield, may still follow a learning curve pattern but this metric will increase rather than decrease as an organization learns and improves. Thus, in some cases, the learning curve equation would be written with a positive coefficient on the learning rate, b.

From the learning rate, a progress ratio can be calculated. Typically the progress ratio, p, is the change in the performance metric, y, when cumulative production is doubled or, mathematically, $p = 2^{-b}$ [Dutton and Thomas (1984)]. Dutton and Thomas performed an assessment across more than 200 empirical studies of progress functions and found that learning rates differ widely not only across different industries, processes, and products but also within the same or similar processes and products [Dutton and Thomas (1984)]. Rates in their analysis varied from 55-107% with a mode at 81-82%. The low end shows an incredible learning rate of decreasing unit costs to 55% of their original value when production was doubled and the high end shows that unit costs actually increased with increasing production volumes.

Firms see productivity gains as they gain cumulative experience and move down the learning curve [Argote and Epple (1990)]. While productivity gains can also come from improvements in machinery, the value of cumulative experience to increasing productivity has been noted in manufacturing since the first documented learning curve [Wright (1936), Argote and Epple (1990)]. The accumulated learning within a firm is often also called organizational knowledge.

1.2 Knowledge Transfer

Knowledge within a firm can be embedded in its people, its technology, or its structure and the ability of a firm to effectively transfer knowledge across these elements within its own organizational boundaries can be a key element of competitive advantage [Argote (1999)].

The type and context of the both the knowledge and the transfer process impact knowledge transfer. Knowledge that is explicit or more codified is more easily transferred than knowledge that is tacit or less codified [Polanyi (1966), Kogut and Zander (1992)]. An additional characterization of knowledge that is difficult to transfer is 'sticky knowledge' where stickiness refers to the additional cost of acquiring and transferring this knowledge [Szulanski (1996), von Hippel (1994)]. Knowledge can be transferred through a variety of mechanisms including training, observation by the knowledge recipient, documentation of structures and routines, and access to technologies where knowledge is embedded [Argote (1999)].

The amount of knowledge transferred across boundaries has been quantified in the case of ship production (cross-location transfer), in the case of truck production (cross-shift transfer), and in the case of 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)].

1.3 Learning Across Products

The majority of organizational learning research focuses on production of a small number of products with minor variations (e.g. aircraft, ships, and trucks) [Alchian (1963), Rapping (1965), Argote and Epple (1990)]. Yet, 87% of US output comes from multi-product firms and over half of all US firms alter their product mix every five years [Bernard et al. (2010)]. Research that looks at learning and product mix shows both advantages and disadvantages to an increase or change in product mix or variety and there is not a clear consensus within the literature as to when and how firms should handle processing a multitude of products simultaneously.

Benefits associated with specialization are even noted back in 1776 in Smith's work in a pin factory [Smith (1776)]. In the early days of production, all products were created using craft production methods where each item was essentially unique [Womack et al. (1990)]. Mass production methods brought the standardization of parts and processes which lowered production costs dramatically and allowed firms to manufacture high volumes of these products [Womack et al. (1990)]. More recent production practices focus on lean production methods and the implementation of flexible manufacturing systems. The lean production system was born from the Toyota Production System and aims to improve end-value to the customer by reducing waste throughout the production process [Womack et al. (1990)]. Each of the primary tenets of the Toyota Production System changes how well a factory is able to handle a variety of products on the production line and what level of product mix is considered acceptable.

The literature on production management and operations research has largely come to the consensus that product variety increases production costs and work in the area focuses on ways to mitigate this increase in cost or decrease in productivity by implementing various production strategies. Empirical results from this literature show changeovers in a multi-product environment can be costly due to 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, planning of material handling and inventory, as well as quality control [Fisher and Ittner (1999)].

Studies have shown different ways to mitigate the negative impacts of product mix including elements of product design, process design, structure of the factory or line setup, and external relationships such as those with suppliers. Designing products with shared components [Fisher et al. (1999)], products that have commonality in their design [Desai et al. (2001)], or products that implement a modular design or have components that may be reused [Suarez et al. (1995)] can all improve plant productivity when working on a production line that sees a mixture of products.

Suarez et al. (1996) also found support for lean practices such as problem solving approaches utilizing worker input, and the use of flexible wage strategies to increase the ability of firms to be flexible. MacDuffie et al. (1996) found lean practices such as a multi-skilled workforce, and product development geared toward manufacturability helped firms in the automotive industry to deal with high levels of product mix and parts complexity. Finally, factories that have strong relationships with external partners have been shown to be better able to deal with product mix on the line. Gaimon and Morton (2005) showed that firms can benefit from working closely with their equipment suppliers in the development of flexible and more efficient tools. Maintaining a close relationship to suppliers can aid in having the supplies and components in place when needed [Suarez et al. (1996), MacDuffie et al. (1996)]. Randall and Ulrich (2001) even found that firms that match their supply chain structure to their product variety strategy faired better than those firms which did not. As work in this area evolves, it will be particularly interesting to see how firms utilize the suite of manufacturing practices available to address the needs specific to their products, industry, and production environments.

Similar to lean production or lean manufacturing is the flexible manufacturing system. Many elements of lean production are implemented within different varieties of flexible manufacturing systems. Suarez et al. (1995) define four types of flexibility which a flexible manufacturing system can possess: product mix flexibility (the number of types of products a system can produce at a given time), new product flexibility (how quickly a new product can be introduced), volume flexibility (the ability to alter production volumes while maintaining efficiency and quality), and delivery time flexibility (how quickly a product can be sent to the end customer). They find that these four first-order types of flexibility capture other orders of flexibility implemented on the production line, such as routing flexibility, programmable equipment, or workers with specific skill sets and that these first-order flexibilities are the types of flexibility that most directly affect a firm's competitiveness. These production systems are evolving to take on more and different types of product variety and complexity in different ways.

On the other hand, not all empirical studies find a negative impact from an increase in product mix. Indeed the organization science literature suggests that in some cases the impact of product mix can be neutral and in many cases positive. One empirical study from the organizational science literature looked at product mix and found a neutral (not statistically significant) impact of product mix in a pizza franchise [Darr et al. (1995)]. Past work on accidents in the airline industry and in lab studies suggest that organizations may learn more from diverse than homogenous experiences [Haunschild and Sullivan (2002), Schilling et al. (2003)]. In manufacturing, Bernard et al. (2010) show that changing the product mix causes firms to more efficiently reallocate resources. Additionally, Wiersma (2007) found that heterogeneity in related products had a positive impact on the learning rate within the Royal Dutch Mail.

One possible answer to this tension of the impact of product mix and variety may have to do with the frequency of specialization and variety. Recent work by Staats and Gino (2011) on the Japanese banking industry found different results when they looked at the impact of variety on worker productivity over a day or over several days. They found that over the course of one day worker productivity increased due to the effects of specialization, however variety (switching tasks) over the course of multiple days improved productivity of the same workers. An additional benefit they found for variety is that workers who saw with a higher variety stayed longer at the firm.

Another possible explanation to the tension of the impact of product mix on learning rates is to consider the definition of multi-product environments across these studies. The few studies in the organization science literature that do look at organizational learning and knowledge transfer in multi-product environments use varying definitions of what constitutes "multi-product". Bernard et al. (2010) use data from the U.S. Manufacturing Census from 1987-1997 to study product-switching. They define product-switching and multi-product firms based on Standard Industrial Classification (SIC) codes gathered in the manufacturing census. Using this metric, they find that a little over one-half of U.S. firms alter their product mix every five years. Another study looked at the extent of product heterogeneity as a factor in determining different learning rates between regions of the Royal Dutch Mail. In this study, product heterogeneity was defined over the seven different types of products within the letter division of the firm (business-to-business/customer letters, customer-to-business/customer letters, post office boxes, bundled deliveries, priority mail, certified mail, or larger quantities (magazines, etc.)) [Wiersma (2007)]. Another study looks at knowledge transfer in the context of transfer across four different models of an airplane with a total production volume of 250 planes [Benkard (2000)]. And yet another study looks at knowledge transfer across franchise locations of a pizza chain and defines product mix by different pizza types (i.e. regular or pan pizzas) in their analysis [Darr et al. (1995)]. In contrast to the Bernard study, in the mail, airplane, and pizza cases, the product mix studied would all fall under the same SIC classification code used in the U.S. Manufacturing Census. In looking at these past studies, it is difficult to know how to compare the results from differences in airplane models to differences in mail sorting or differences across SIC classification codes.

In trying to unpack the question of why product mix may have more negative consequences in some contexts than others, it is helpful to look at potential knowledge transfer between (or across) different products. Past research on the extent of knowledge transfer between different models or product generations has been mixed. On the one hand, Benkard (2000) utilizes a dataset that includes several models of airplanes built simultaneously on the same production line and finds that there are substantial spillovers from one model to the another. However, in the case of knowledge transfer across DRAM generations Irwin and Klenow (1994) find weak results about knowledge transfer. In their analysis they assume that knowledge only transfers from the most recent generation to a current generation and, thus, that knowledge depreciates completely after two generations. Their results show that knowledge transfer is statistically significant in five of seven generations but only economically significant (producing a non-trivial impact on production experience) in two of those generations. Looking ahead, it will be particularly interesting to explore further what leads to knowledge transfer occurring in some cases and not others.

This tension between the operations management literature on the negative consequences of product mix and the organizational science literature noting the potential benefit of product mix and diversity of products for an organization's learning rate raises important research questions about these cases in which product mix may harmful and these in which product mix may be beneficial for organizational learning.

1.4 Measures of Product Mix

Within the production and operations management literature, product mix and variety can have different definitions and measures. In the automobile industry, studies have looked at the impact of component sharing in automotive braking systems [Fisher et al. (1999)] on plant productivity and also at the impact of model mix complexity, parts complexity, option content,and two measures of option variability [Fisher and Ittner (1999), MacDuffie et al. (1996)] (in the authors' definition, options are elements or features of the automobile that are presented to the customer and may or may not affect the core design of the automobile for the manufacturer). In the printed circuit board industry, Suarez et al. (1995) looked at mix flexibility as measured by four variables: "1) the number of different board models assembled by each plant, 2) the number of different board sizes used during assembly, 3) the range of board density handled by each plant, and 4) the number of product categories (e.g., VCRs, televisions, and stereos) in which the boards were used." In the case of the bicycle industry, work has looked at variation across attributes of the bicycle such as those of the frame (material, geometry and size, and color) in addition to other components [Randall and Ulrich (2001)]. Finally, Kekre and Srinivasan (1990) look at product line breadth based on self-reported data from the PIMS (Profit Impact of Marketing Strategies) database in their analysis of over 1,400 business units (most of which are part of a *Fortune* 500 firm). These different measures all provide unique insights into the interactions between product variety and productivity.

Studies that have looked at the impact of product mix or heterogeneity have used the

Herfindahl Index to aggregate data across all types of products or tasks into a single term which allows more specific insights on the impact of product mix heterogeneity than a simple share variable would allow [Wiersma (2007), Staats and Gino (2011)]. The Herfindahl Index, or Herfindahl-Hirschman Index, is traditionally used a measure of diversity of firm sizes within a given industry. The Herfindahl Index, H, is the sum of squared shares, s, of the variable of interest.

$$H = \sum_{i=1}^{N} s_i^2 \tag{1.3}$$

Traditionally the variable of interest, i, is firms, though the measure has been extended to products and tasks as well. The Herfindahl Index has been found to have a few issues with bias when using citation data for patents due to the nature of the underlying data [Hall (2005)], however our data gives us exact counts and this certainty prevents the bias issue.

The most notable alternate quantification of mix or entropy is the Shannon Index [Shannon (1948)]. This entropy measure is:

$$H_{Shannon} = -\sum_{i=1}^{N} s_i \log s_i \tag{1.4}$$

This measure is not appropriate in our case or similar cases where products are introduced later in the timeframe and have a share of zero for certain observations.

The quantification of product mix into this singular variable, the Herfindahl Index, is insightful in analyses as it can capture shifts in product heterogeneity across multiple product types, unlike a share variable which focuses on the impact of a singular product group. Each of these types of shifts in product mix heterogeneity could be important in untangling the impact of product mix on productivity and learning rates.

Chapter 2

Research Context, Data, and Methods

2.1 Research Context

This work studies organizational learning and knowledge transfer in a leading firm within the high technology hardware component industry. The focus firm is U.S. owned and began moving its production overseas to an in-house manufacturing facility in a developing country in 2001. My analysis will draw on data from the manufacturing facility in the developing country.

2.1.1 Firm and Products

The focus firm is one of the leading revenue earners within its industry. The firm began the move of production from the U.S. to the developing country in 2001 and by 2004 all of the products had been transferred to the production facility in the developing country. This facility has manufactured five types of focus products, comprising 86% of their total production volume, and fourteen types of non-focus products, comprising 14% of total production volume, between 2001 and 2011.

The focus products are products that are similar in form factor and type of end use, but capture the evolution of the products and technology over time. The firm considers these products its main priority and considers itself a leader in this market. The market for these five products is relatively predictable compared to the markets of the remaining products in the firms portfolio. The focus products are expected to improve every cycle (6-18 months) and customers will plan appropriately. Finally, the firm considers these products to be "...products that are actually similar enough [to each other for comparison], but we have to make incremental improvements every cycle" [Denomme, Interview August 29, 2011]. The non-focus products are a mixture of product types with different underlying end-uses for customers, different form factors based on industry standards, or based on a different implementation of the underlying technology. Some of these non-focus products had significantly longer ramp-up times because of slow demand and some saw a large capital investment from the firm because large volumes were anticipated.

There are two additional layers of product variation beyond the basic five types of focus products and fourteen types of non-focus products. At the first level, each of the five focus products can be broken into two categories – these categories are based on specific end-use application and each require specific components. At the second level, customers of the firm often request specific variations on these base product types including tailored performance specifications, additional required tests, or cosmetic alterations (such as label placement). Each product and customized product produced by the firm receives a part number. The facility has manufactured 1,139 specific variations across the five types of focus products and 5,818 specific variations across the fourteen types of non-focus products as measured by unique part numbers.

2.2 Data Collection

In the process of collecting data on the firm I spent a total of nineteen days at the manufacturing facility. I spent two days from April 10-11, 2008 on an initial site visit with my dissertation advisor, Erica Fuchs. I followed this initial trip with two extended site visits focused on data collection. The first data collection trip included seven days at the factory from July 23-August 1, 2008. The second data collection trip included ten days at the factory from October 9-21, 2011. During each of the data collection trips I collected quantitative and qualitative data. Quantitative data includes firm archival records on sales orders, production volumes, and employment records. Qualitative data includes observation of and participation on the production floor; interviews with managers, engineers, and trainers; and surveys given to engineers.

2.2.1 Quantitative Data

Over its history this factory has kept detailed records of production volumes and yields, sales orders and shipments, labor hours worked, and employment histories of all its employees.

While on-site I focused on collecting four types of quantitative data: process-step yields for selected production, total labor hours worked, total production volume seen by the factory, and production start dates for the chosen products which may have started production prior to the more offshore. Additionally, in followup interviews I acquired quantitative data on the sales and shipment volumes of products from the offshore facility. Details about each type of data collected by the firm, and provided to me for the purposes of this study, are given in Figure 2.1.

Data Source	Sales & Shipment Reports	Human Resources Employment Database	Production Floor Tracking System	Hard Copies of Weekly Hours Report	Backlog Database
Data Details	Volume of each order and date the order was placed, requested, scheduled for shipment, and actually shipped	Date that each of the factory's over 20,000 employees was hired, resigned, promoted, or changed shifts/ supervisors	Start and output production volumes broken down by: shift, product, process step, test station, and operator	Weekly hours worked by rate and division	Similar to the sales and shipment reports yet specific to orders that have not yet been completed.
Data Availability	2000 – 2011	2001 – 2011	2004 – 2009	2004 – 2008	2006 – 2008
Calculated Variable(s)	Shipment & Order Volumes (q_t, Q_t, K_t), Product Mix (s_t, H_t), Instruments	Labor Input (L_t)	Per-step production volumes & product mix	Labor hours	Indicator of production backlogs

Figure 2.1. Overview of quantitative, archival data sources.

Analysis between the first data collection site visit and the second data collection site visit showed that the shipment tracking data were an excellent match to the production floor tracking data and that employment levels were an excellent match to the weekly hours data. The shipment data and employment history data were available from 2000 and 2001, respectively, which is farther back than their counterparts. Thus, I focused on collected an updated version of each of these datasets for continued analysis. The employment database tracks each employee's hire date, resignation date, and any promotions or changes in position at a daily level. The sales and shipment tracking database tracks details of all orders the factory receives, manufactures, and ships and includes data on these dates and order volumes. We aggregate the data from the employment and sales order databases into weekly values for our analyses.

In order to manage the large amount of data collected, I implemented a MySQL database and imported all quantitative data. MySQL provided flexibility in manipulating the unformatted production data into weekly per-product yield calculations, in calculating weekly shipment and order volumes by different product groupings, and in calculating weekly employment levels from the employment history data. I wrote PERL scripts to access the MySQL database and extract the needed data.

2.2.2 Qualitative Data

Over the course of the three site visits, I spent a total of nineteen days in the production facility, twelve hours observing the production floor, and an additional two hours actually participating on the production line (assisted by a trainer). I performed forty-four semi-structured interviews with managers, engineers, and trainers. An additional thirteen engineers filled out surveys (see details in Section 2.2.2.1). These observations and interviews were transcribed, along with my regular interactions with employees throughout the day, observations from a weekend outing spent with two employees, and interactions over the course of twenty-four meals shared with employees, into 112 typed pages of notes. All transcriptions were completed within at least forty-eight hours, the vast majority within twenty-four hours. Figure 2.2 details the types of qualitative data collected on the site visits.

Site Visit & Data Collection Overview	
Preliminary Site Visit	2 days
First Data Collection Site Visit	7 days
Second Data Collection Site Visit	10 days
Production Floor Observation	12 hours observation 2 hours participation
Semi-structured Interviews	8 with VP 30 with engineers/managers 6 with trainers
Surveys	13 engineers
Field Notes	112 typed pages
Archival Data Records	17.5GB of data from production and human resources databases from as early as 2000

Figure 2.2. Overview of qualitative data collection.

2.2.2.1 Surveys

I worked with the primary engineers to establish a process listing for our focus products which covered seventy-seven different processes across the selected focus products. Once the process list was defined, I distributed surveys to additional engineers that asked engineers to rank process difficulty by product; estimate the commonality of machinery, trainers, technicians, and engineers across focus products; and general questions about commonalities across products. These questions included the engineer's perception of what makes products similar and their experience with implementing new products on the production line.

The processes cover three stages of production: assembly, testing, and final prep. Different engineers are responsible for each of these stages of production. A total of eleven engineers filled out the survey with the following distribution: three assembly engineers, five testing engineers, three final prep engineers. All engineering-based process data used in out analysis is based on the responses of these eleven engineers. Of the seventy-seven total processes defined for the focus products, one process was unknown to the surveyed engineers. Two additional engineers filled out the survey for sections of the factory responsible for producing subcomponents. A sample of the survey given to engineers can be found in Appendix A.

I also used a modified version of the process survey to perform focused interviews with three trainers. In this case I talked through each process step with the trainer and asked for a process categorization and average training time for each process. One head trainer is responsible for the three stages of production listed above within the primary production line. All training process data used in our analysis came from a focused interview with this trainer. Of the seventy-seven total processes defined for the focus products, three processes were unknown to the trainer. Additionally, I interviewed two other trainers responsible for sections of the facility which produce subcomponents. A sample of this modified survey which served as the core of the focused interviews can be found at the end of Appendix A.

2.3 Measures & Data Characterization

2.3.1 Production Output Volume

We were able to collect two different kinds of data on production. One set came from the production floor tracking database and one set came from the firm's shipment records. There are two primary limitations to the data from the production floor tracking database: 1) the floor tracking data is only available beginning in 2004 while the shipment records are available back through 2001 and 2) the actual production volumes of products are tricky to extract from the floor tracking database given how process results are logged in the system – the most accurate production measure is the volume logged in the highest volume test for a given part number-order which is a close but not perfect measure for actual production volume. We found a strong match between the two measures and the extended availability of the shipment measure is a distinct advantage given how important early experiences are in determining learning curves. We utilized the shipment data as our primary production output volume measure in our subsequent analyses.

Figure 2.3 shows weekly shipment volumes as well as direct labor employment levels, on which there is more information in Section 2.3.3.

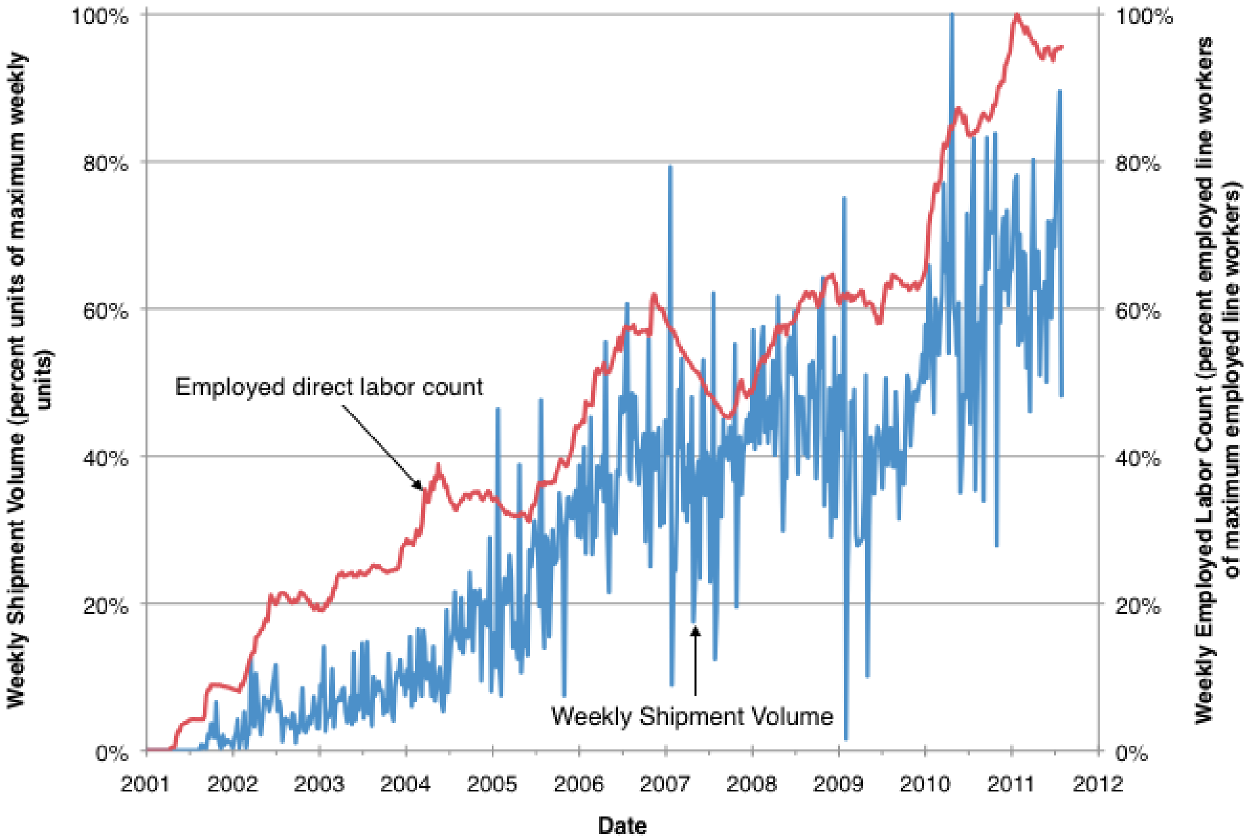

Figure 2.3. Weekly shipment volume and direct labor employment levels.

2.3.2 Product Groupings & Product Mix

To quantify product mix we utilize the measures detailed in Section 1.4 – the share of certain product groupings and an aggregate measure, the Herfindahl Index.

Using the shipment data detailed in Section 2.3.1 we can calculate shipment volumes by product grouping. Figure 2.4 shows the shares of shipment volume over time by each of the focus product groupings and the non-focus product grouping.

Figure 2.5 shows the shares of non-focus shipment volume over time for each type of non-focus product. Each colored block in the plot is a unique non-focus product grouping. More details on the product differences of these types can be found in Section 5.1.1.

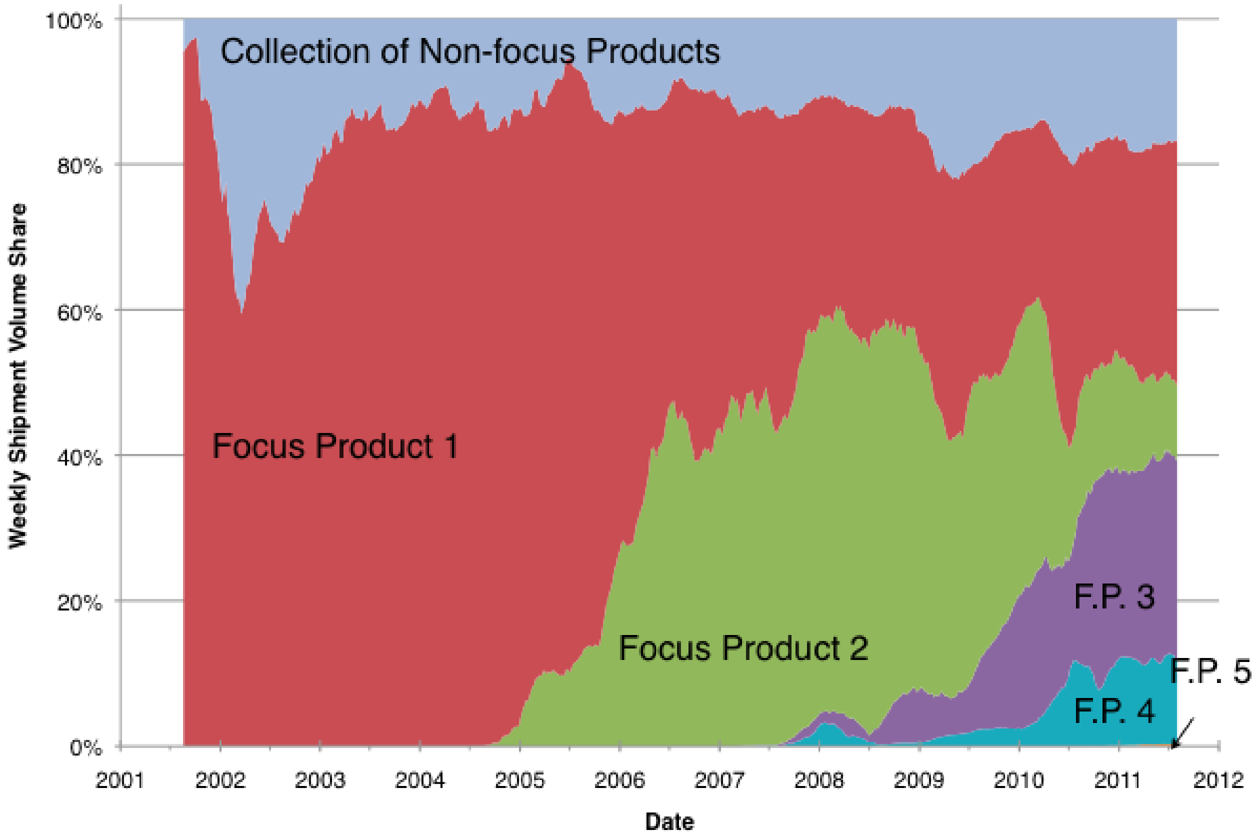

Figure 2.4. Product grouping shares of weekly shipment volume for generations of the focus product and the collection of non-focus products.

The Herfindahl Index, H, is a weighted average of the shares of different product groupings so it incorporates both the number of different types of products produced as well as the quantity of each of these products. It is calculated as

$$H_t = \sum_{i=1}^{6} \left(\frac{q_{it}}{q_t} \right)^2 \tag{2.1}$$

Notably, when the Herfindahl Index is equal to or close to 1 there is a low mix of products and when it is close to 0 there is a high mix of products.

We can also exclude the sixth product grouping of non-focus products to generate a

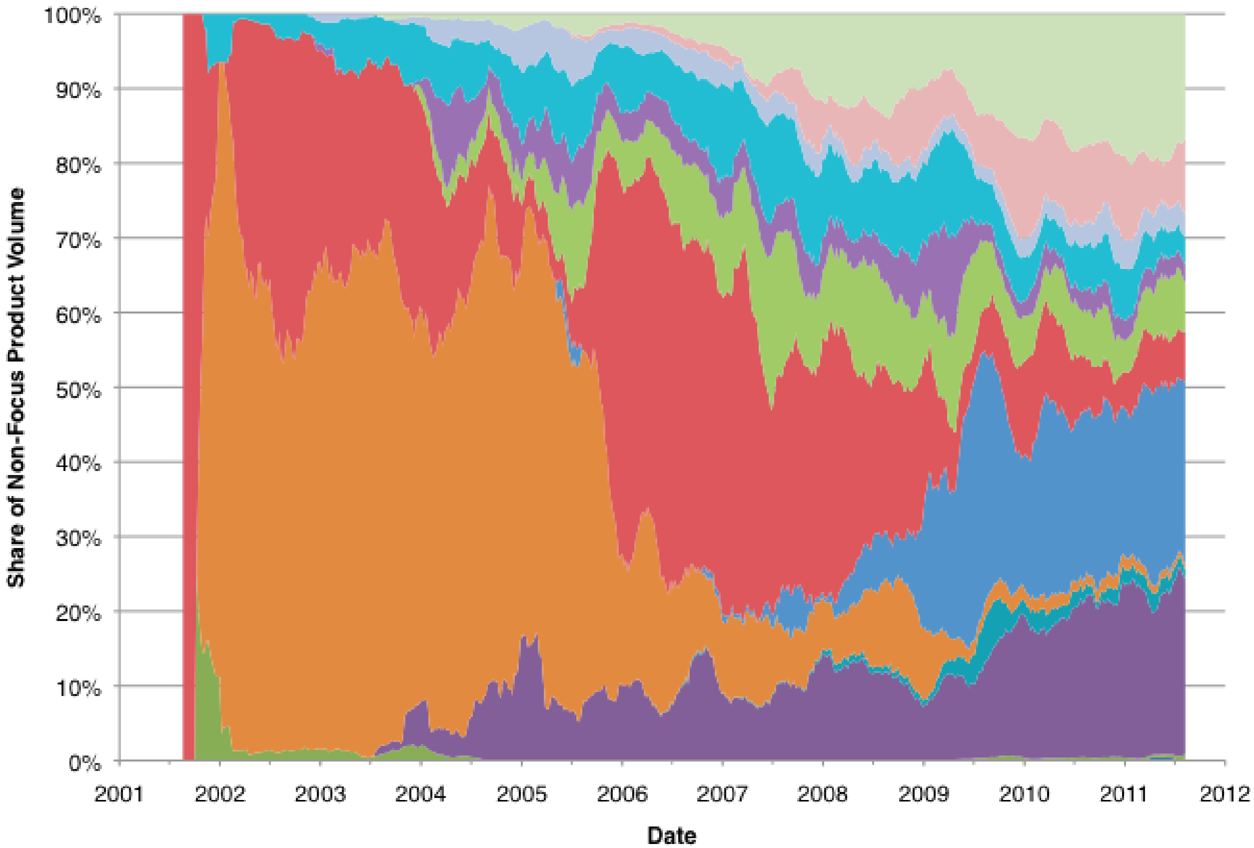

Figure 2.5. Non-focus product grouping shares of weekly shipment volume.

measure of the mix of focus products

$$H_{focus,t} = \sum_{i=1}^{5} \left(\frac{q_{it}}{q_t} \right)^2 \tag{2.2}$$

Figure 2.6 shows a plot of the two calculations of the Herfindahl Index over time.

2.3.3 Labor Input

The employment database includes detailed information on each of the firm's employees including the employee's position and dates that each employee was hired, promoted, resigned

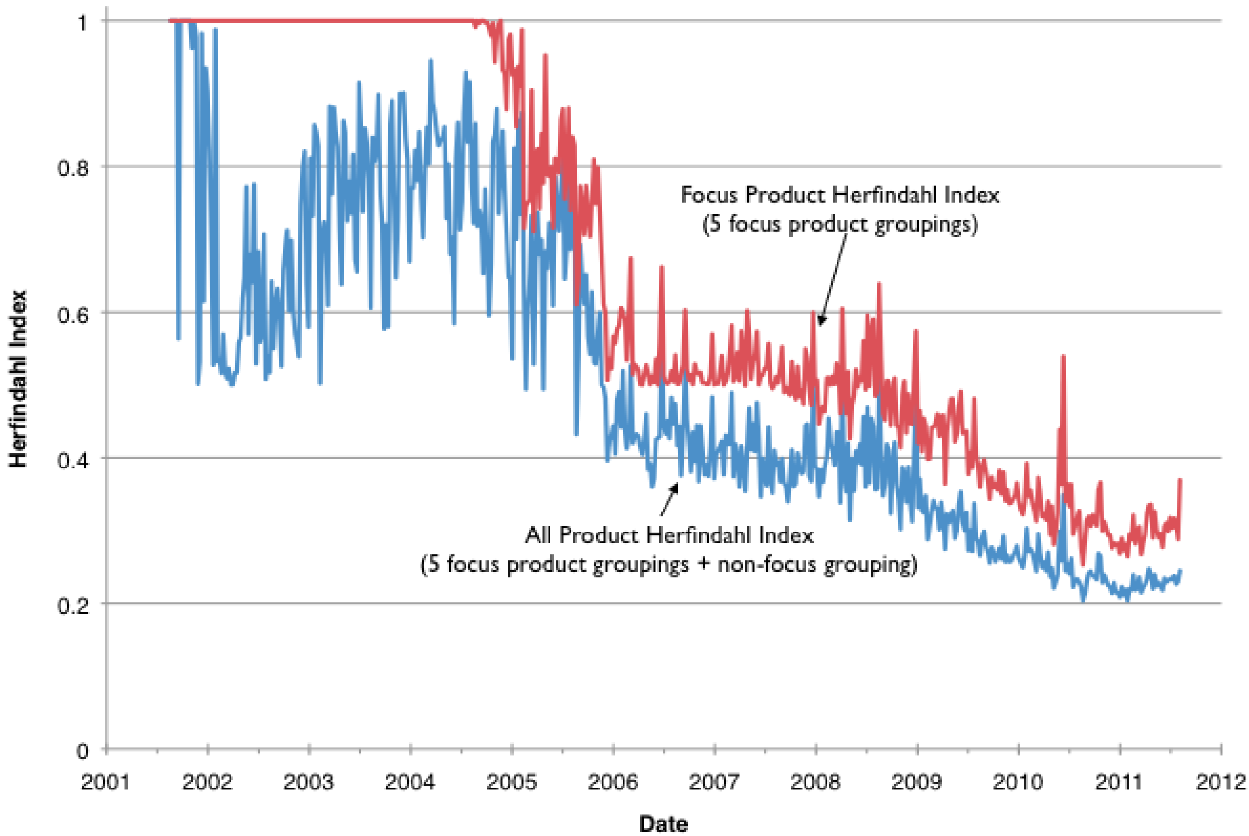

Figure 2.6. Weekly Herfindahl Index.

or changed shift or supervisor. We worked with the human resources department of the firm to aggregate each of the firm's 133 positions into specific labor type groupings and then again into broader labor type groupings. A breakdown of these groupings is shown in Figure 2.7. We were able to collect data on labor hours from the firm, but the data were only available from 2004-onward. Thus we used the count of direct laborers employed as our weekly labor input variable. Figure 2.3 shows a plot of this variable over time[1].

[1]To our knowledge, no other studies looking at learning use a labor count as an input measure, but, as noted, we see a correlation, $\rho = 0.76$, between labor hours and employee count for the time period for which we have overlapping data. Many studies use labor hours as labor input data [Epple et al. (1996), Argote et al. (1990)] and some use payroll as an alternate for labor input [Ton and Huckman (2008)]. Our results are robust to the use of either labor input measure.

Labor Type Broad		Labor Type Specific	Position Examples
Direct Labor	On-the-Line	Line Worker	Production Operator, Manufacturing Specialist
		Line Worker w/ Add'l Responsibility	Line Leader, Quality Auditor
		Line Supervisor	Production & Line Supervisors
	Trainers	Trainer	Trainers
Indirect Labor	Technical	Engineers	Various Levels of Engineer (w/ Bachelors degree)
		Technician	Various Levels of Technician (w/ ~Associates degree)
		Technical Management	Principal Engineers, Technician Managers
	Non Technical	Top Management	Manager III, Director, Sr. Director, VP
		Middle Management	Manager I, II
		Individual Contributor	Accountant, HR, Planning, Buyers
		Clerical/Administrative	Clerical, Personal Secretary, Personal Assistant

Figure 2.7. Breakdown of labor types.

2.3.4 Capital-In-Use

We worked with the firm's industrial engineering department to collect data on the number of machines in use by production stage on the factory floor as well as cost data of these machines. The firm's accessible records provide data from 2005-2011 and unfortunately not for 2001-2004. Figure 2.8 shows the capital in use for the final production stage.

The timeframe of the capital in use data limits the inferences we can make on learning and knowledge transfer as it eliminates the critical early years of learning and knowledge creation at the factory. We found our results in the following analyses to be robust to inclusion of the capital in use measure over the shorted timeframe.

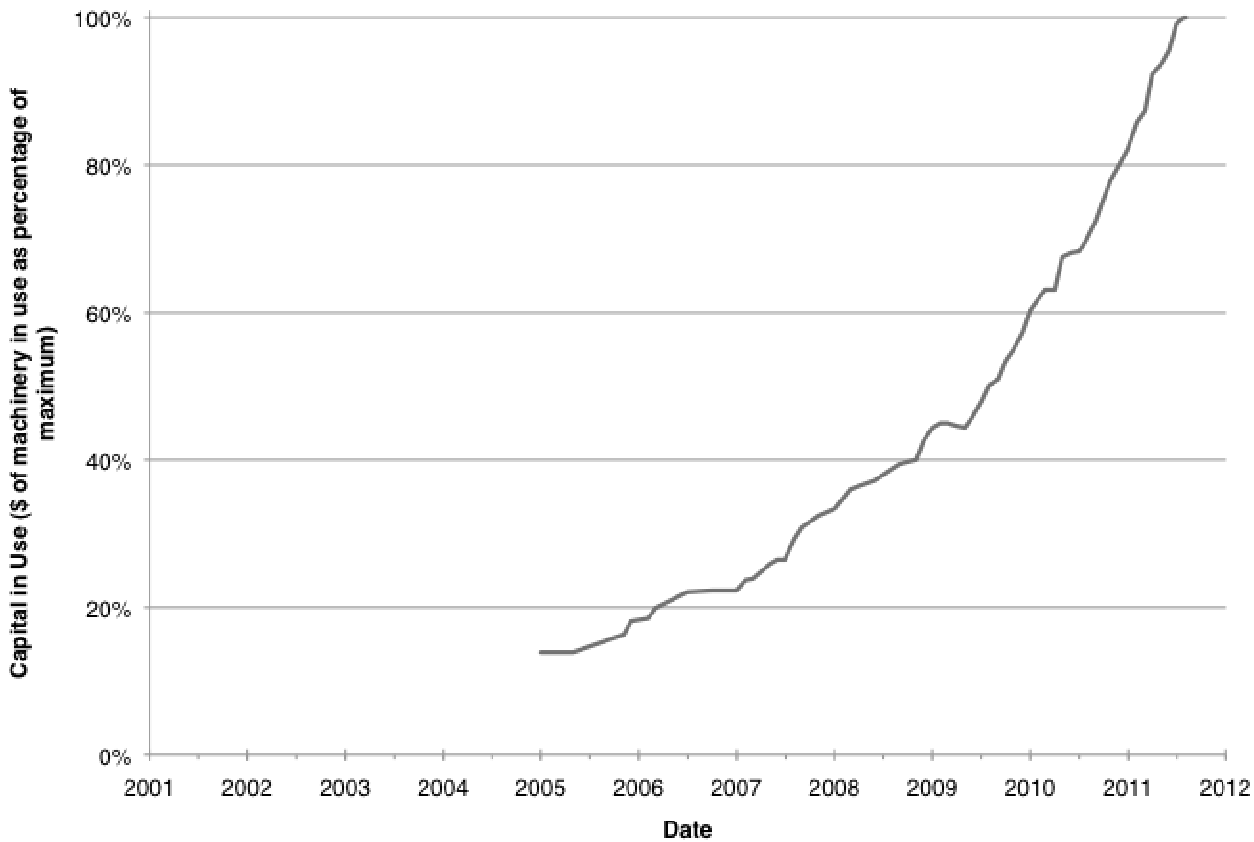

Figure 2.8. Capital in use in final production stage.

2.4 Empirical Models

In order to analyze the quantitative data collected, find the organization's learning rate, test the impact of product mix, and learn about knowledge transfer we built several econometric models. We begin with the traditional learning model and then expand this model to incorporate a knowledge transfer component. These models are detailed in Sections 3.2 and 4.2.

Chapter 3

Organizational Learning: Results & Discussion

3.1 Overview

For this study we have collected both qualitative and quantitative data on the production of hardware components from a manufacturing facility in a developing country of a leading manufacturer in the industry. We have performed analyses of this data to understand its structure and have implemented several specifications of an econometric model to understand the dynamics on the production floor regarding the role of organizational learning. This chapter details the foundational organizational learning model, results from the model, and conclusions drawn from these analyses.

3.2 Foundational Learning Model

To find the organization's learning rate we estimate a production function that incorporates learning by doing, a generalization of the traditional learning equation (equation 1.2):

$$\ln(q_t) = \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_3 \ln(L_t) + \epsilon_t \tag{3.1}$$

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, and ϵ_t is the error term [Argote (1999)].

We expanded this model to allow the learning rate to vary over time by adding in a quadratic experience term:

$$\ln(q_t) = \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_2 \ln(Q_{t-1})^2 + \beta_3 \ln(L_t) + \epsilon_t \tag{3.2}$$

To look at the impact of variety across focus and non-focus products we added a variable of the percentage or share of non-focus products shipped in week t, s_t:

$$\ln(q_t) = \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_2 \ln(Q_{t-1})^2 + \beta_3 \ln(L_t) + \beta_4 s_{Nonfocus,t} + \epsilon_t \tag{3.3}$$

To look at the impact of heterogeneity within focus products we added the focus-product

Herfindahl Index, $H_{focus,t}$, to the model:

$$\ln(q_t) = \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_2 \ln(Q_{t-1})^2 + \beta_3 \ln(L_t) + \beta_5 H_{focus,t} + \epsilon_t \tag{3.4}$$

Finally, we look at a model with both measures of product variety – share of non-focus products and Herfindahl Index of focus products:

$$\ln(q_t) = \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_2 \ln(Q_{t-1})^2 + \beta_3 \ln(L_t) + \beta_4 s_{Nonfocus,t} + \beta_5 H_{focus,t} + \epsilon_t \tag{3.5}$$

Table 3.1 summarizes the interpretation and our expectation of each parameter.

Table 3.1. Parameter definitions and expectations for foundational learning model

Parameter	Interpretation	Expectation
β_0	Intercept of the production function	–
β_1	Elasticity of production output with respect to cumulative experience in equation 3.1	$\beta_1 > 0$
$\beta_1 + 2\beta_2 \ln(Q_t)$	Elasticity of production output with respect to cumulative experience in equation 3.2	$\beta_2 \leq 0$
β_3	Elasticity of production output with respect to the number of line workers employed	$\beta_3 > 0$
β_4	Elasticity of production output with respect to the share of non-focus products	$\beta_4 < 0$
β_5	Elasticity of production output with respect to the the focus-product Herfindahl Index	?

3.3 Results

Results on organizational learning are shown in Table 3.2. We estimate each model using weekly data. Models 1 and 2 build the base learning model by estimating the impact of lagged production experience (cumulative output) on productivity as a linear relationship and then adding a quadratic term to allow the learning rate to differ over time. Model 3 tests the impact of product mix as measured by the share of non-focus products. Each of these models was estimated using ordinary least squares with Newey-West robust standard errors, which are robust to the potential presence of heteroskedasticity and/or autocorrelated errors.

Table 3.2. Estimation results: Foundational learning model.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
β_1, Experience	0.5479***	3.7942***	2.0426***	4.1482***	2.3987***
$\ln(Q_{t-1})$	(0.0700)	(0.4503)	(0.6911)	(0.4060)	(0.4689)
β_2, Experience Sq.		-0.1032***	-0.0476**	-0.1181***	-0.0624***
$(\ln(Q_{t-1}))^2$		(0.0149)	(0.0238)	(0.0136)	(0.0152)
β_3, Labor	0.2056	0.5615***	0.4812*	0.5096*	0.4310*
$\ln(L_t)$	(0.1844)	(0.1898)	(0.2692)	(0.2617)	(0.2299)
β_4, Share Non-focus			-1.9144***		-1.9035***
$\alpha_{Nonfocus,t}$			(0.3046)		(0.2952)
β_5, Focus Herf.				-0.7461***	-0.7275***
$H_{Focus,t}$				(0.3388)	(0.3740)
Observations	461	461	461	461	461
R^2	0.8345	0.8596	0.8763	0.8635	0.8800
Durbin-Watson	1.5361	1.8173	1.9583	1.8721	2.0047

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. Newey-West standard errors are used and are reported in parentheses. The constant term is omitted for firm confidentiality.

We can compare models 1 and 2 to determine the shape of our focus firm's learning curve and establish the proper base model for our remaining analyses. We began with the traditional learning model, model 1, and subsequently added the quadratic term in model 2 to allow the learning curve more flexibility. The results with the quadratic term are presented in model 2 in Table 3.2. The quadratic term is statistically significant as shown by the p-value of the β_2 coefficient ($p < 0.001$). These results indicate that while the firm does learn, their learning rate plateaus over time. We can calculate the maximum peak for the contribution of learning to productivity from the experience and experience squared terms, β_1 and β_2, and we find this peak is beyond the firm's final level of cumulative products shipped in our data. Hence, learning by doing continues throughout the entire period for which we observe data for the firm.

We also estimated this model with a cubic term on the logged cumulative experience variable to allow for a more nuanced change in the learning curve, but did not find that the cubed experience term was statistically significant.

Additionally, in model 2 we can see the labor input term is positive and statistically significant at the 1%-level. All results are robust to the addition of week of quarter controls which would capture any shipping or scheduling variations throughout the quarter.

Figure 3.1 shows the contribution of cumulative experience to current period productivity in each of the models. This figure illustrates that learning continues over the entire period of production. The comparison of model 1 to the more comprehensive model 5 shows that the baseline (model 1) understates the rapidity of learning during the initial years of production

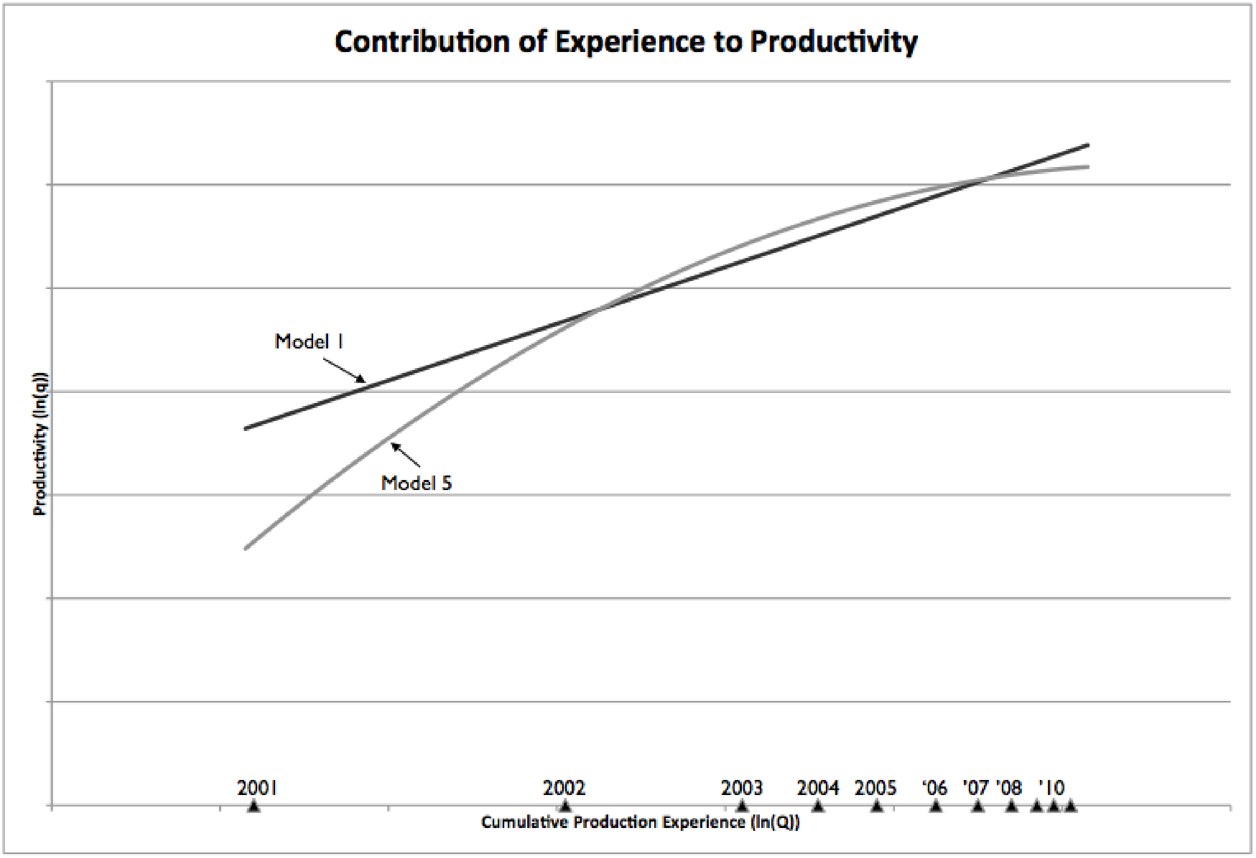

Figure 3.1. Comparison of learning models: shape of learning curve.

while also failing to capture the gradual slowing of learning as production progresses.

3.3.1 Impact of Product Mix

We look at the percentage share of non-focus products, $s_{Nonfocus,t}$, as our first measure of product mix on the production line. With the share of non-focus products, model 3, we see that an increase in the share of non-focus products decreases production line productivity. This insight comes with a 1%-level statistical significance on the non-focus product share term.We found no significant interaction between the non-focus product share variable and the experience measure.

The second measure of product mix on the production line is the focus-product Herfindahl Index, $H_{focus,t}$. The coefficient on the focus Herfindahl Index, β_5, is negative in the model 4 indicating that a higher mix of focus products increases productivity.[1] This result is robust to the inclusion of the share of non-focus products as shown in model 5. These results suggest that we see a decrease in productivity from increased production of the non-focus products, but that increased variation within the focus products is helpful for productivity.

Models 2 through 5 of Table 3.2 provide evidence of the effects of controlling for the shape of the learning curve and product mix. We see the estimated learning rate is lower, by examining β_1 and β_2, when we control for share other in model 3, and higher when we control for our focus-Herfindahl in model 4. When we account for both share other and focus-Herfindahl in model 5, we see the estimated learning rate is about the same level as when we do not account for these elements of product heterogeneity. This suggests that improvements in the focus products are perhaps being counteracted by the challenges of producing non-focus products. The significance of both share non-focus and the Herfindahl confirm the importance of including both of these measures of product heterogeneity. Figure 3.2 shows how controlling for the product mix reduces the estimated decline in the rate of learning.

As with models 1 and 2, all results are robust to the addition of week of quarter controls which would capture any shipping or scheduling variations throughout the quarter.

[1] Recall that, as product heterogeneity increases, the Herfindahl Index decreases.

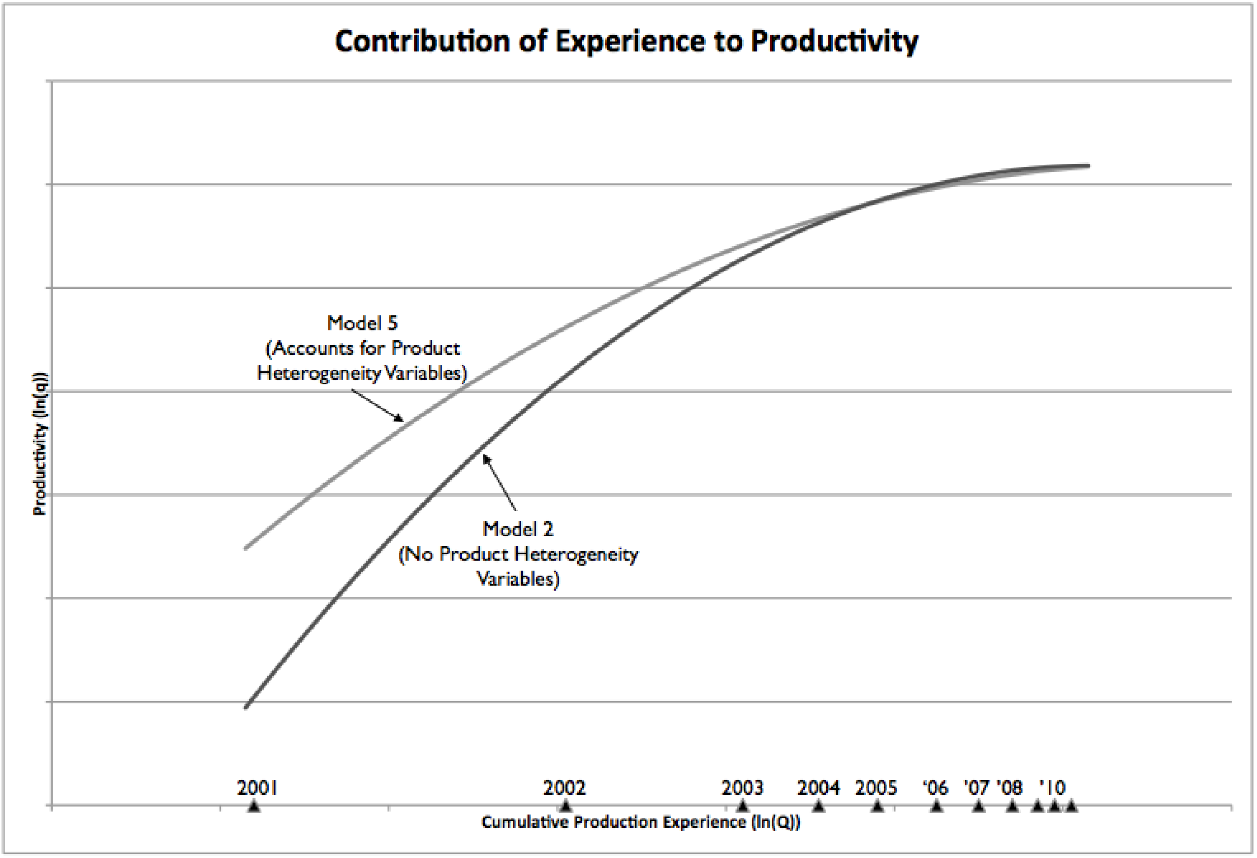

Figure 3.2. Comparison of learning models: impact of product heterogeneity variables.

3.3.2 Endogeneity

One might be concerned about endogeneity in our product mix variables if the focus firm intentionally alters their product mix in a given week – for example, that they save up the non-focus products to produce in a week where there is less demand for focus products. To address this we ran a two stage least squares model using order placement product mix variables (share non-focus and focus Herfindahl) to instrument for the product mix shipment volume measures. Order placement is driven by customer demand and is not controlled or metered by the focus firm, thus it is exogenous to the firm in general, and specifically to the production line.

Table 3.3. Estimation results: Instrumented foundational learning model.

Variable	Model 6
β_1, Experience	2.4374***
$\ln(Q_{t-1})$	(0.4240)
β_2, Experience Sq.	-0.0640***
$(\ln(Q_{t-1}))^2$	(0.0135)
β_3, Labor	0.4254***
$\ln(L_t)$	(0.1542)
β_4, Share Non-focus	-1.9023***
$\alpha_{Nonfocus,t}$	(0.3037)
β_5, Focus Herf.	-0.8086**
$H_{Focus,t}$	(0.3158)
Observations	461
R^2	0.8800
Durbin-Watson	2.0042

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. Newey-West standard errors are used and are reported in parentheses. The constant term is omitted for firm confidentiality.

We included six weeks of order lags as instruments, averaged in two-week intervals, as six weeks is the average order fulfillment time for the firm. We found that order-placement variables were strong instruments and that the focus product Herfindahl Index was endogenous, but we do not reject the hypothesis that the non-focus product share is exogenous[2]. Hence, we estimate our model instrumenting for the Herfindahl Index but not for the share

[2]The Durbin-Wu-Hausman test gives a p-value of 0.045 for the share non-focus instrumentation showing that our product mix variables are exogenous at the 5% level. The Cragg-Donald F-statistic is 17.960 for the share non-focus instrumentation showing that the orders are strong instruments at the 5% level using the Stock-Yogo critical values.

of non-focus products. The estimates are presented in Table 3.3. The estimates exhibit a modest increase in the estimated coefficient of the Herfindahl and little change in the other coefficients.

3.4 Conclusion

Our firm learns and its productivity improves with increasing experience. The firm's learning rate gradually slows over time, but the firm does indeed continue to learn from its experiences throughout the course of our analysis. An increase in share of non-focus products decreases the productivity of the firm. An increase in the heterogeneity of focus products increases productivity of the firm. These results are robust to time controls which capture shipping or scheduling variations. The results are also robust to any concerns about endogeneity.

It is particularly interesting to note the difference between the impact of focus/non-focus product variety and heterogeneity within focus products. Our results show that these two types of product mix yield different impacts on productivity, a distinction not found in either the organizational science or operations management literature. These results could shed insights into the tension in those bodies of literature by suggesting that some variation in product mix is helpful as long as those variations in product types are not too different. When there is variation in related products, it may allow the firm to learn from these minor variations either through the line workers performing the same or closely related production process steps, thus leveraging the accumulated knowledge of the firm, or through the development of newer versions of products or process steps by embedding the production knowledge into tools or the products themselves. When the firm tries to vary the product mix too much though, in our case by increased share of non-focus products, these products or related process steps may be too different to effectively leverage the accumulated production knowledge of the firm. Notably, there may be other benefits from revenue or profits from these non-focus products which may offset the productivity losses for the firm.

The positive impact of increased variation in focus products might suggest that the firm is able to transfer knowledge about production of focus products across the different types of focus products. Another explanation of this result could be that focus products have differing levels of production processes in common and these commonalities may serve as conduits of knowledge transfer across products. In the next three chapters, we explore the extent to which knowledge transferring across products may be contributing to the positive impact of heterogeneity across generations of focus products and the role that process commonality and difficulty may play in the mix of products on the production line.

Chapter 4

Knowledge Transfer: Results & Discussion

4.1 Overview

This chapter expands on the modeling work on organizational learning by building and testing an econometric model of the transfer of knowledge across products. By leveraging detailed data about the production of each product type we are able to shed additional insights on the impact of focus/non-focus product variation and heterogeneity of focus products by investigating transfer across focus and non-focus products and across different generations of focus products.

4.2 Learning Model with Cross-Product Knowledge Transfer

The knowledge transfer model builds on the foundational learning model detailed in section 3.2 by replacing the experience term with a knowledge term that incorporates transfer of experience with other types of 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

$$\begin{aligned} &\ln(q_t) = \beta_0 + \beta_1 \ln(K_{t-1}) + \beta_3 \ln(L_t) + \beta_4 s_{Nonfocus,t} + \beta_5 H_{focus,t} + \epsilon_t \\ &\text{where } K_t = \sum_i s_{it} K_{it} \\ &\qquad K_{it} = Q_{it} + \gamma (Q_t - Q_{it}) \\ &\qquad s_{it} = \frac{q_{it}}{q_t} \end{aligned} \tag{4.1}$$

where q_t is the current period production volume, K_{t-1} is a lagged knowledge parameter, and L_t is the current count of employed line workers. The knowledge parameter, K_t, is the weighted production experience across specific product types, s_{it} is the production share of product type i, K_{it} is the product specific knowledge, and Q_{it} is the cumulative production volume for product i.

The model is built such that all product specific volumes and characteristics are expressed in the product specific knowledge term, K_{it}. We alter this term with a product specific knowledge transfer term, γ_i, to investigate the asymmetry of knowledge transfer, as detailed below.

$$K_{it} = Q_{it} + \gamma_i \left(Q_t - Q_{it}\right) \tag{4.2}$$

The knowledge term allows each product to accumulate a knowledge base of its own, K_{it}. This allows each product to learn from its own past production and also to learn from the production of other products – or transfer knowledge from these other products. We can expand this farther still by allowing each product grouping to contribute differently to other product groupings. We utilize four different transfer parameters, and thus allow three different opportunities within the model for products to transfer knowledge from other products. These parameters allow transfer from non-focus products to focus products ($\gamma_{NonFocus2Focus}$), from focus products to non-focus products ($\gamma_{Focus2Non}$), from older focus products to newer product products ($\gamma_{Old2New}$), and from newer focus products to older focus products ($\gamma_{New2Old}$). It is instructional to fully specify the breakdown of the knowledge terms in the models presented here:

$$\begin{aligned}
K_{1t} &= Q_{1t} + \gamma_{New2Old}\left(Q_{2t} + Q_{3t} + Q_{4t} + Q_{5t}\right) + \gamma_{NonFocus2Focus} Q_{nonfocus} \\
K_{2t} &= Q_{2t} + \gamma_{Old2New}\left(Q_{1t}\right) + \gamma_{New2Old}\left(Q_{3t} + Q_{4t} + Q_{5t}\right) + \gamma_{NonFocus2Focus} Q_{nonfocus} \\
K_{3t} &= Q_{3t} + \gamma_{Old2New}\left(Q_{1t} + Q_{2t}\right) + \gamma_{New2Old}\left(Q_{4t} + Q_{5t}\right) + \gamma_{NonFocus2Focus} Q_{nonfocus} \\
K_{4t} &= Q_{4t} + \gamma_{Old2New}\left(Q_{1t} + Q_{2t} + Q_{3t}\right) + \gamma_{New2Old}\left(Q_{5t}\right) + \gamma_{NonFocus2Focus} Q_{nonfocus} \\
K_{5t} &= Q_{5t} + \gamma_{Old2New}\left(Q_{1t} + Q_{2t} + Q_{3t} + Q_{4t}\right) + \gamma_{NonFocus2Focus} Q_{nonfocus} \\
K_{nonfocus,t} &= Q_{nonfocus,t} + \gamma_{Focus2Non}\left(Q_{1t} + Q_{2t} + Q_{3t} + Q_{4t} + Q_{5t}\right)
\end{aligned} \tag{4.3}$$

where K_1–K_5 represent the knowledge pools for focus product groupings 1-5, respectively, and $K_{nonfocus}$ is the knowledge pool for the grouping of non-focus products.

We restrict $\gamma_{Focus2Non}$ to equal the average of all other gammas:

$$\gamma_{Focus2Non} = \frac{\gamma_{New2Old} + \gamma_{Old2New} + \gamma_{NonFocus2Focus}}{3} \tag{4.4}$$

The production processes of products are often finalized once mass production has begun, which would suggest that there might be little or no opportunity for knowledge transfer backward. However, from the process commonality and difficulty measures detailed in Chapter 5, we might expect knowledge to transfer through the processes which are common across generations of focus products in either direction (forward or backward). Thus, we do not restrict the backward transfer parameter, $\gamma_{New2Old}$, to zero.

4.3 Results

Results on cross-product knowledge transfer are shown in Table 4.1. As with the learning results, we estimate each model using weekly data. These models were estimated using maximum likelihood. Models 7–9 build the base knowledge transfer model and model 10 includes an instrumented focus product Herfindahl Index.

In all models we see that the knowledge parameter, K_{t-1}, is positive and statistically significant indicating that our focus firm's cumulative weighted production experience is beneficial to weekly productivity and serves as a knowledge base. A more detailed discussion

Table 4.1. Estimation results: knowledge transfer model.

Variable	Model 7	Model 8	Model 9	Model 10 Instrumented
Transfer: Non-Focus→Focus	-2.3727***	-2.5352***	-2.5391***	-3.7101***
$\gamma_{NonFocus2Focus}$	(0.2937)	(0.4443)	(0.6341)	(0.3393)
Transfer: Older Focus→Newer Focus	2.3346***	2.5388***	1.1352***	1.0647***
$\gamma_{Old2New}$	(0.5211)	(0.5298)	(0.4387)	(0.3956)
Transfer: Newer Focus→ Older Focus	-0.6683	=0	=0	=0
$\gamma_{New2Old}$	(0.5496)			
β_1, Knowledge	0.4022***	0.3790***	0.3436***	0.3907***
$\ln(K_{t-1})$	(0.0369)	(0.0372)	(0.0463)	(0.1285)
β_3, Labor	0.3524***	0.3881***	0.3225***	0.3360***
$\ln(L_t)$	(0.1144)	(0.1155)	(0.1231)	(0.0457)
β_4, Share Non-focus	-2.1682***	-2.2863***	-2.2451***	-2.2759***
$s_{Nonfocus,t}$	(0.1910)	(0.1892)	(0.1951)	(0.2074)
β_5, Focus Herf.			-0.6478**	-2.2524***
$H_{Focus,t}$			(0.2566)	(0.0116)
Observations	461	461	461	461
R^2	0.8516	0.8512	0.8521	0.8516
Durbin-Watson	1.9732	1.9687	1.9747	1.9499

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. Standard errors are used and are reported in parentheses. The constant term is omitted for firm confidentiality.

of the weights across products within the knowledge term follows below. Additionally, we see that in each model the labor input term, L_t is also positive and statistically significant. All results are robust to the inclusion of controls for calendar time which would capture general technological improvements and robust to the inclusion of week of quarter controls which would account for any shipping or scheduling variations throughout the quarter.

4.3.1 Knowledge Transfer Across Products

Our results show that knowledge does transfer across products and does so differently across different product groupings. We see that knowledge transfers from older focus products to newer focus products ($\gamma_{Old2New}$), knowledge does not transfer from newer focus products to older focus products ($\gamma_{New2Old}$), and we see that production of non-focus products is detrimental to the knowledge base ($\gamma_{Nonfocus2Focus}$).

In model 7 we see that $\gamma_{New2Old}$ is not statistically significantly different from 0, thus we set $\gamma_{New2Old} = 0$ to reduce the number of terms estimated in models 8–10. When we account for the focus-product Herfindahl Index we see the coefficients on the transfer parameters drop to a magnitude around 1 (compare model 8 to models 9 and 10). The interpretation here is that products are still learning the same amount from production of older products that they are from production of their own products.

4.3.2 Impact of Product Heterogeneity

Both of our measures of product mix, the focus product Herfindahl Index and the share of non-focus products, are still significant in the knowledge transfer model. This confirms that product mix effects do have an impact on the current period productivity. The transfer parameters shed additional insights on the impact of different products on the cumulative production knowledge base.

That the coefficient on share of non-focus products and the transfer parameter from non-focus to focus products are both negative and statistically significant shows that non-focus products diminish current period productivity and also have a negative impact on learning by diminishing the base of knowledge stored from cumulative production.

As in the learning model, the focus product Herfindahl Index has a negative and statistically significant coefficient. This corresponds to a positive impact on current period productivity due to the directionality of the Herfindahl Index. We also instrument the focus product Herfindahl Index with the order flow focus product Herfindahl Index, as in the organizational learning model, and see consistent results (see model 10).

4.4 Conclusion

Our firm is able to transfer knowledge across certain product types. The firm is able to utilize 100% of their past production experience with older focus products to aid in the production of new focus products. Production of older focus products is neither aided nor harmed by the production of newer focus products. An increased heterogeneity in focus products on the line is still beneficial for overall firm productivity beyond the knowledge that is transferred across focus products. However, the firm does not transfer knowledge across focus and non-focus product types.

Non-focus products are detrimental to the firm's productivity in multiple ways. An increased share of non-focus products in a given week decreases firm-productivity. Beyond the immediate negative impact on firm productivity, the production of non-focus products degrades the total knowledge base from which the plant draws upon for future production of all product types. Again, these products may be profitable enough for the firm to outweigh these productivity losses.

It is notable that in both the case of focus/non-focus products and across focus product generations, our product heterogeneity variables are still significant when we account for the the transfer of knowledge. This indicates that even though the firm is learning in a more sophisticated way than modeled in our foundational learning model, the results about the positive impact of increased variation of generations of focus products and a negative impact of increased share of non-focus products are robust. This suggests that there is perhaps more happening beyond the transfer of knowledge that explains how variation of focus product generations is beneficial to the firm.

The finding that knowledge is transferring differently across different types of products may help alleviate some tension surrounding mixed results about transfer across products found in the few studies that look at this in the literature. We find support for transfer across related products but not for transfer across products that are too different. The extent of differences in products is an important distinction here. The following chapter delves more specifically into the differences across focus and non-focus products.

While the knowledge transfer model allows for production of one product to have an impact on the knowledge base utilized for another specific product, looking at process information will dig into production differences in a different way. Examining how similar the production processes are may add additional depth the types of knowledge that may be embedded in the common knowledge base utilized by the firm.

The next chapter, Chapter 5, will also delve into process commonality across focus products and process difficulty for focus product processes. Chapter 6 will incorporate these process elements back into the learning and knowledge transfer models presented in the previous chapter and this chapter to shed additional insights on how the firm is able to transfer knowledge so successfully across focus products as well as the positive impact of increased heterogeneity across generations of focus products.

Chapter 5

Product and Process Commonality and Difficulty

This chapter sheds insights on the findings from the organizational learning and knowledge transfer models based on the focus firm's products and the underlying production processes.

5.1 Product and Process Commonality

5.1.1 Product Commonality: Focus and Non-Focus Products

As described in Section 2.1.1, focus products are similar to each other in form factor and type of end use and make up the vast majority of volume of the factory (86% of total shipped volume in units shipped) while non-focus products are a mixture of different types of products and make up the minority of total volume of the factory (14% of total shipped volume in units shipped). Specifically, there are fourteen basic types of non-focus products: three variations on the focus product form factor, one grouping of subcomponents sold directly, one accessory product, eight alternate form factors, and a collection of miscellaneous products. Table 5.1 details for each of these groupings: the shipment volumes as a percentage of cumulative shipped volume, number of distinct part numbers (a measure of variety within specific product types), and physical volume relative to the primary focus product form factor. The relative physical volume measure is meant to give the reader a sense of how different these form factors truly are from each other; note the range of relative physical volume from 0.1–9.0. While the underlying technology across all of these products is based on the same scientific principles, the end products across these non-focus groupings are dramatically different not only from the focus products, but also each other.

There are two form factors within our focus products. They are labelled FF1 and FF2 in Table 5.1. Focus form factor 1 (FF1) is the primary and original form factor for our focus product type. Focus products 1 and 2 are form factor 1. Focus form factor 2 is an evolution of focus form factor 1. Focus products 3, 4, and 5 are form factor 2. Both of these form factors are industry standards. The following section goes into much more depth on the implications of these different form factors and the related impacts on production processes. The evolution of our focus products (from product 1 through 5) are generations of a product where new technologies or advancements are integrated into the newer versions to meet changes in market demand.

Given the variety of different products within the non-focus product grouping, we perhaps

Table 5.1. Comparison of focus and non-focus products.

Focus or Non-Focus Products	Form Factor	Percentage of Cumulative Shipped Volume	Number of Distinct Part Numbers	Physical 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
Non	Focus Variation 1	3.16%	2,227	1.0
	Focus Variation 2	1.95%	127	1.2
	Focus Variation 3	0.16%	11	1.0
	Subcomponent	2.03%	109	0.1
	Accessory	1.87%	5	1.1
	Non Focus 1	1.79%	385	3.1
	Non Focus 2	1.55%	1,862	1.9
	Non Focus 3	0.73%	51	6.7
	Non Focus 4	0.11%	14	8.2
	Non Focus 5	0.10%	14	1.3
	Non Focus 6	0.05%	157	9.0
	Non Focus 7	0.02%	17	5.5
	Non Focus 8	0.01%	25	0.5
	Miscellaneous	0.72%	977	–

should not be surprised that we find that an increased share of non-focus products decreases current period productivity in both the learning model and the knowledge transfer model. The variation within non-focus products is great with over 14 different form factors and with 5,981 product variations (part numbers) compared to the 1,139 variations (part numbers) within the focus products. Additionally, the non-focus products are greatly different than our focus products with relative physical volume ratios of non-focus products ranging from 0.1 to 9.0 times the size of the focus products. Recall that the knowledge transfer model also showed that increased production of non-focus products had a negative impact on the firm's cumulative knowledge base. The considerable variety of these non-focus products is likely to require a multitude of different resources – machinery, engineers, manufacturing processes and related training staff, in addition to sourced materials. These impacts may be captured in the longer-term knowledge measure.

5.1.2 Process Commonality: Focus Products

In this section we delve into the manufacturing process steps to gain a better understanding of the extent of commonality between our focus products.

During the final extended site visit I worked with engineers to collect process flow sheets for selected focus products. Recall from Section 2.1.1 that each of the focus products has two variations based on end-use applications and that these different variations require specific components. We call these variations A and B. Variation B is considered by the firm more complex than variation A. Variation B also sees a significantly smaller demand and, as such, has a much smaller production volume – variation A makes up 77% of total shipment volume while variation B makes up 9% of the total shipment volume. I collected process flow sheets for each of the following products: 1A, 1B, 2A, 2B, 3A, 3B, 4A, and 4B. At the time of the final extended site visit, focus product 5 was still a very new product and was primarily in the product development stage with a very small production volume, thus I did not collect process flow sheets for focus product 5.

I compiled each of the process listings into a master list of seventy-seven processes. There are twelve processes which every focus product goes through. The average number of processes per product is thirty-six. This gives a base line level of process commonality between any two products of around 33% depending on the exact number of processes. These statistics are summarized in Table 5.2

Table 5.2. Focus product process commonality summary statistics

Process Commonality Summary Statistics	
Total Processes across Focus Products	77
Common Processes	12
Average Processes per Product	36
Approximate Baseline Percent of Processes that are Common	33%

Comparing process commonality across each pairing of focus products yields the matrix shown in Table 5.3. The cells of the matrix are color coded to identify different levels of commonality; green cells have a low-level of process commonality at 0-50%, yellow cells have a medium-level of process commonality at 51-75%, and pink cells have a high level of process commonality at 76-100%. Generally, there is a high level of process commonality across focus products 1 and 2[1] and a high level of process commonality across focus products 3 and 4. There is a low level of process commonality between the older products (products 1 and 2) and the newer products (products 3 and 4). Notably, products 1 and 2 are form factor 1 (FF1) and products 3 and 4 are form factor 2 (FF2), which accounts for some of the process differences. However, across these two form factors, around 41% of processes are common.

We know from the production management and operations literature that commonality in design or in components across products is a key factor in lean manufacturing practices used to mitigate the negative impacts of increased product heterogeneity. Thus, the level of process

[1]Notably, product 2B has a medium-level of commonality with products 1A, 1B, and 2A. Product 2B is the most technologically advanced of products 1 and 2 and thus some of the processes are altered beyond the suite of common processes.

Table 5.3. Focus Product Process Commonality Matrix

	1A	1B	2A	2B	3A	3B	4A	4B
1A								
1B	88%							
2A	98%	90%						
2B	72%	74%	74%					
3A	45%	38%	43%	39%				
3B	40%	35%	38%	39%	90%			
4A	41%	37%	39%	40%	94%	91%		
4B	48%	43%	45%	46%	85%	93%	87%	

commonality we see across generations of products may account for the positive impact we see of product heterogeneity for both long-term learning and current-period productivity for our focus products in our learning model. Additionally, the extent of common processes may be a key element of positive knowledge transfer across focus products that we found in our knowledge transfer model. Commonality in elements (such as processes or components) can provide a defined place where the firm can embed and perhaps more easily transfer knowledge. A more thorough understanding of the different types of processes and which types of processes are more or less common may add additional insights into this result as the firm may be more or less able to embed knowledge into different types of processes. We use measures of process difficulty to generalize across processes and to investigate the role of process differences.

5.2 Process Difficulty

To better understand each of the processes, we used interviews and a survey to collect three different measures of process difficulty: engineering rank, training time, and training categorization[2]. Each measure gives unique insight into the processes and the impact on current period productivity and the ability serve as repositories of knowledge.

Recall that the processes established from the process commonality section above, cover three stages of production: assembly, testing, and final preparation. We present results for each of the difficulty rankings broken down by these stages of production.

5.2.1 Sample Processes

To aid the reader in thinking about these processes in the following sections, I first detail in Table 5.4 four different types of processes and how they are each measured in the respective difficulty rankings.

Table 5.4. Sample Processes and Difficulty Metrics

Production Stage	Process	Trainer Categorization	Training Time	Engineering Rank
Stage 1: Assembly	Manual Assembly	Skill	2 days	3.00
Stage 1: Assembly	Soldering	Skill	1 week	4.00
Stage 2: Testing	Performance Test	Simple	3-4 days	1.32
Stage 3: Final Prep	Visual Inspection	Criteria	2 weeks	3.67

The manual assembly process requires a line worker to manually attach two components together, a skill-based process that only takes 2 days to train a line worker. The soldering process is also skill-based, but as soldering is a more complex skill it has a longer training time of 2 weeks and also a higher engineer difficulty ranking of 4.00. The performance test is considered a simple process as all the line worker must do is place the product in the testing machinery and the machinery takes care of the testing process. This process sees a

[2]A description of the survey can be found in Section 2.2.2.1. The full survey can be found in Appendix A.

low training time of 3-4 days and a low engineering difficulty ranking of 1.32. The visual inspection process step requires the line worker to physically examine the product under a microscope and check for specific problems that may have occurred during production. It takes 2 weeks for line workers to train on this process and they must know which problems to look for on which products. In interviews, engineers remarked that they view this process as difficult because they must rely on the line worker to check for all problems and they cannot build a machine to automatically check for issues.

5.2.2 Engineering Rank

Data on engineering rank per process was collected through one specific question on the survey: "Please rate each process step for each grouping of products based on difficulty for the line worker on a scale of 1-5 where 1 is very simple, 2 is simple, 3 is neutral, 4 is difficult, and 5 is very difficult" followed by a table listing all known processes and spots for ranking for each of the eight focus products. All engineers gave the same difficulty rankings across all product types, thus we only present difficulty per process step and not difficulty per process step per product. I averaged across the engineers' process rankings for each process to get an engineer-rank value for each process. Table 5.5 shows statistics for the per-process ranking.

Table 5.5. Engineer Rank Summary Statistics

	Number of Processes	Average Engineer Rank	Variance	Minimum	Maximum
Stage 1: Assembly	50	3.04	0.47	1.33	4.33
Stage 2: Testing	8	2.23	0.55	1.33	3.00
Stage 3: Final Prep	19	2.98	0.74	2.00	4.33
Overall	77	2.95	0.58	1.33	4.33

Figure 5.1 shows a histogram of process rankings across all three stages of production with the following grouping definitions: simple processes (average engineer ranking 1-2.49), neutral processes (average engineer ranking 2.5-3.49), and difficult processes (average engineer ranking 3.5-5). The majority of all processes fall in the neutral range. The trends of stage 1

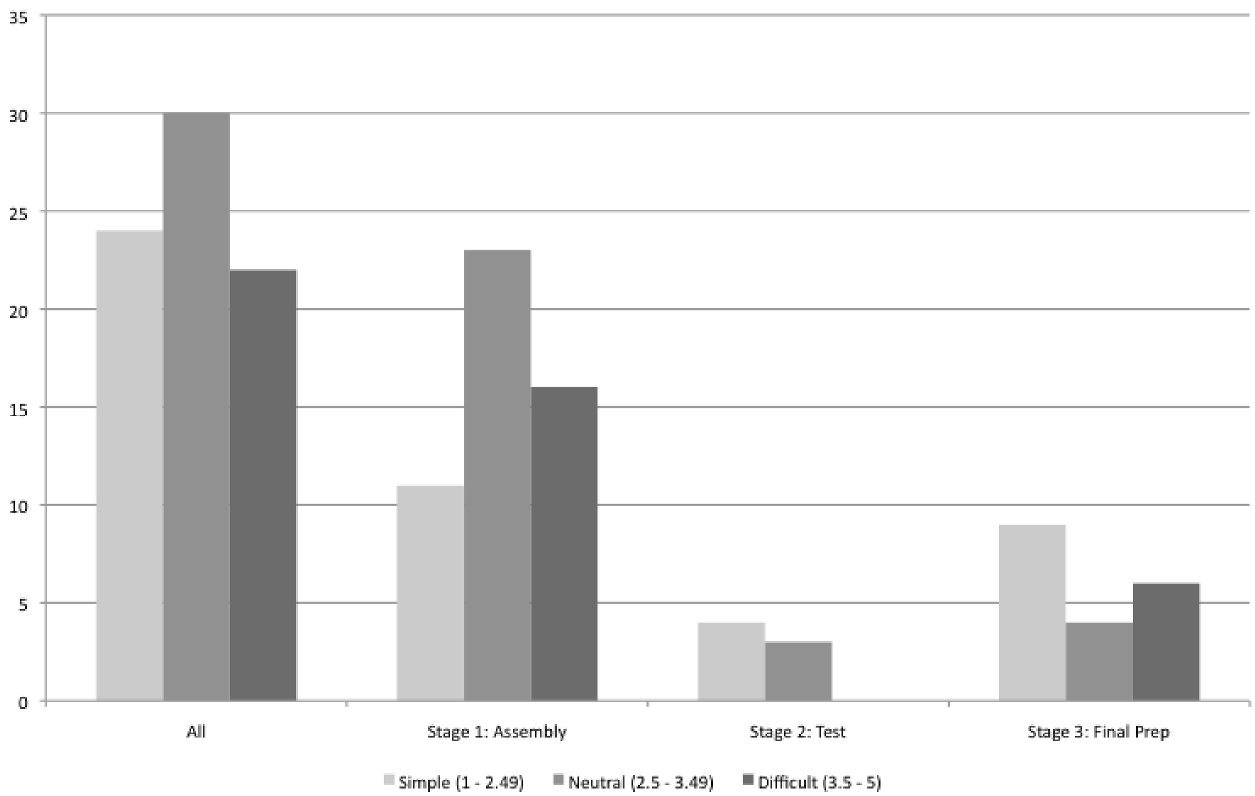

Figure 5.1. Histogram of processes by engineer difficulty ranking.

drive the trends of all processes as stage 1 holds the majority of all processes (50 of 77 total processes). Notably the distributions of stages 2 and 3 differ from those of stage 1. In stages 2 and 3 most processes fall in the simple ranking category.

5.2.3 Training Time

Based on focused interviews with the primary trainer, we know that it takes a range of times to train new employees on the variety of processes. The training times for the processes for our focus products range from 5 minutes to 2 weeks (10 work days). Table 5.6 shows further statistics about training times.

Table 5.6. Training Time Summary Statistics

	Number of Processes	Average Training Time	Variance	Minimum	Maximum
Stage 1: Assembly	49	2.9	6.5	0	10
Stage 2: Testing	6	5.0	2.4	4	8
Stage 3: Final Prep	16	5.8	15.8	0	10
Overall	71	3.7	9.6	0	10

Most (56%) of the processes take less than 4 days of training, however the different production stages have different distributions of training times, shown in Figure 5.2. Stage 1 processes are condensed toward shorter training times with the highest concentration of training times at the very-short level. Of the six known stage 2 processes, five take a medium length of time to train and one falls in the long training time categorization. Stage 3 processes have the highest concentration of processes which take a long time to train. These per-stage process training times aggregate to give the highest concentration of training time in the short (2-4 days) range.

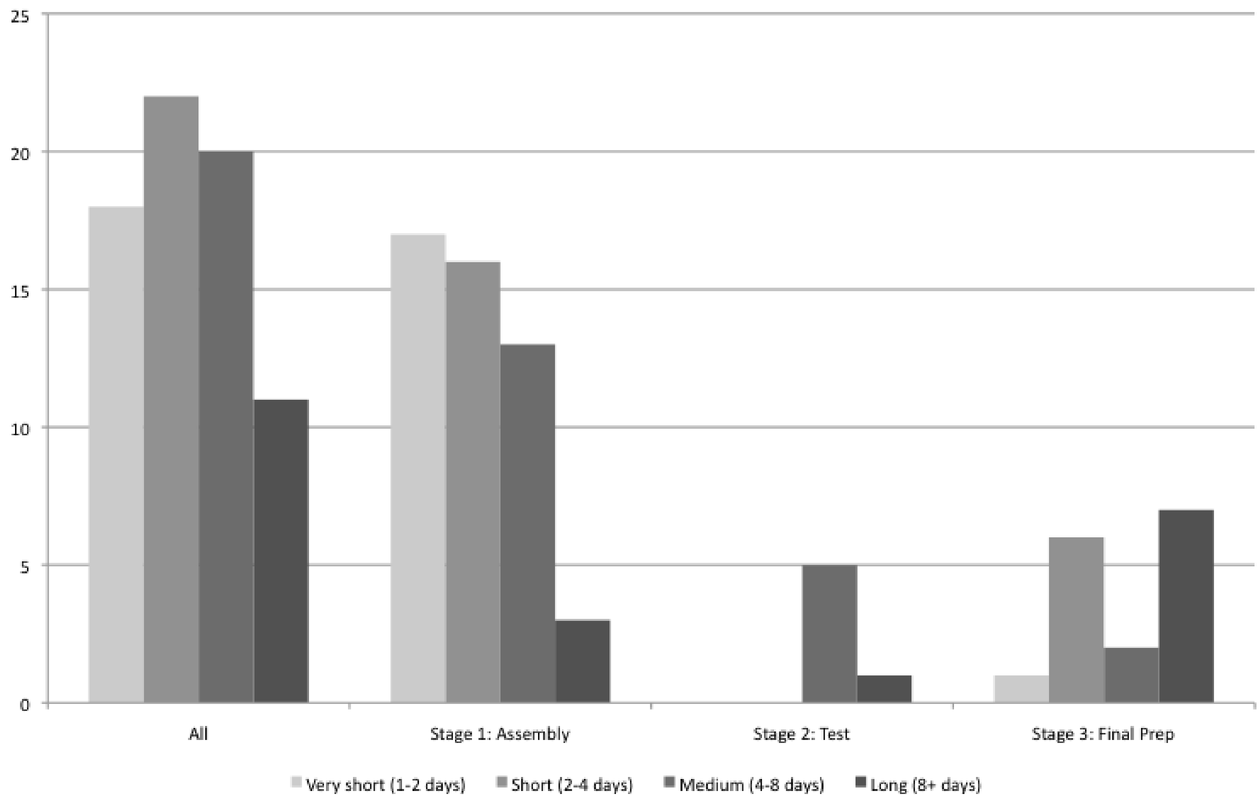

Figure 5.2. Histogram of processes by training time.

5.2.4 Training Categorization

The training department roughly categorizes each of the processes into a type of process. These categorizations are simple, criteria-based, and skill-based processes. In general, simple processes don't require that much skill to perform, criteria-based processes require the line worker to visually inspect products and/or perform the process based on different observable characteristics, and skill based processes require skill development (such as soldering or learning to use particular machinery/tooling). There are a few critical processes that trainers pay particular attention to in the training process. Most of the processes are skill-based with the next highest concentration as simple processes. A breakdown of the categorization is shown

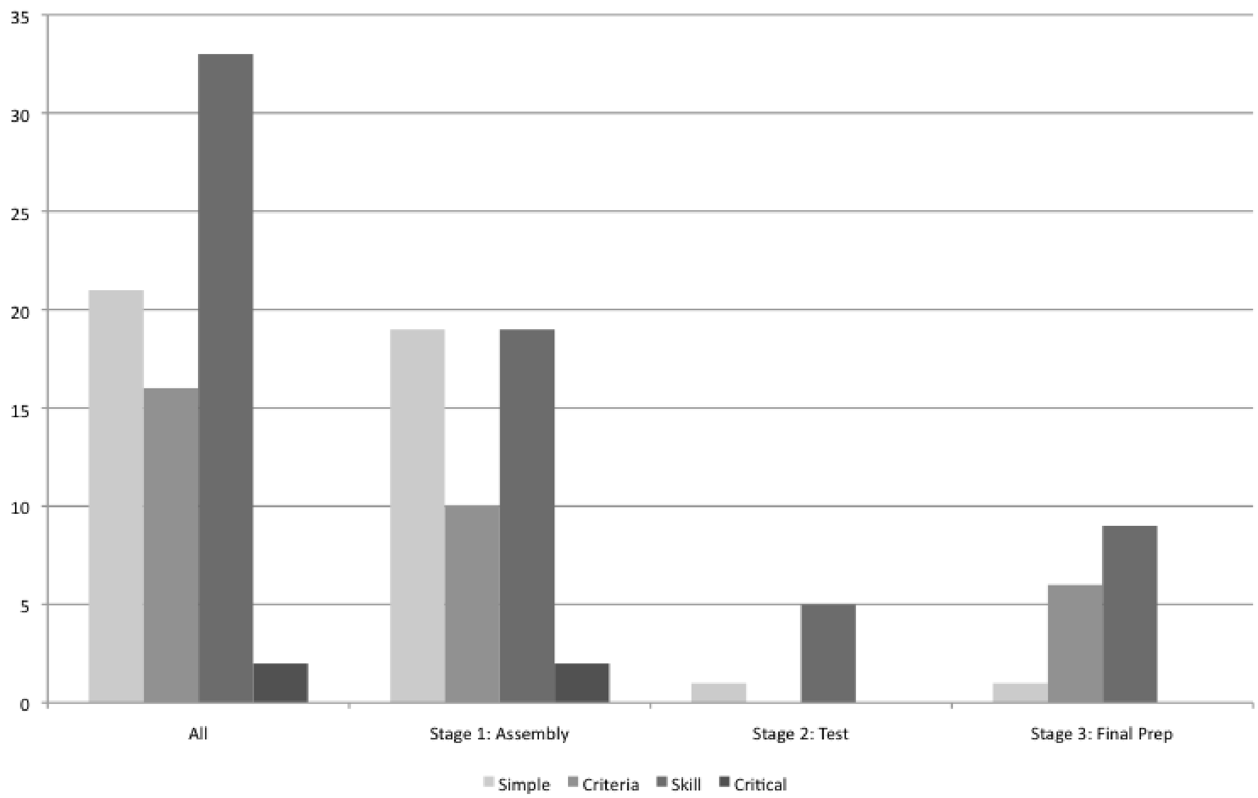

Figure 5.3. Histogram of processes by trainer categorization.

in Figure 5.3.

5.2.5 Comparison Across Metrics

While the descriptive statistics above provide initial insight into how processes differ from each other, we can gain additional insight when we compare the different difficulty measures to each other. Each of the sections below discusses a pairing of the difficulty metrics. For each comparison, we focus on the aggregate processes rather than the processes broken down by stage of production.

5.2.5.1 Training Time and Training Categorization

In general, training time and trainer-categorization map quite well to each other, as shown in Figure 5.4. Most trainer-categorized simple processes also have a very short training

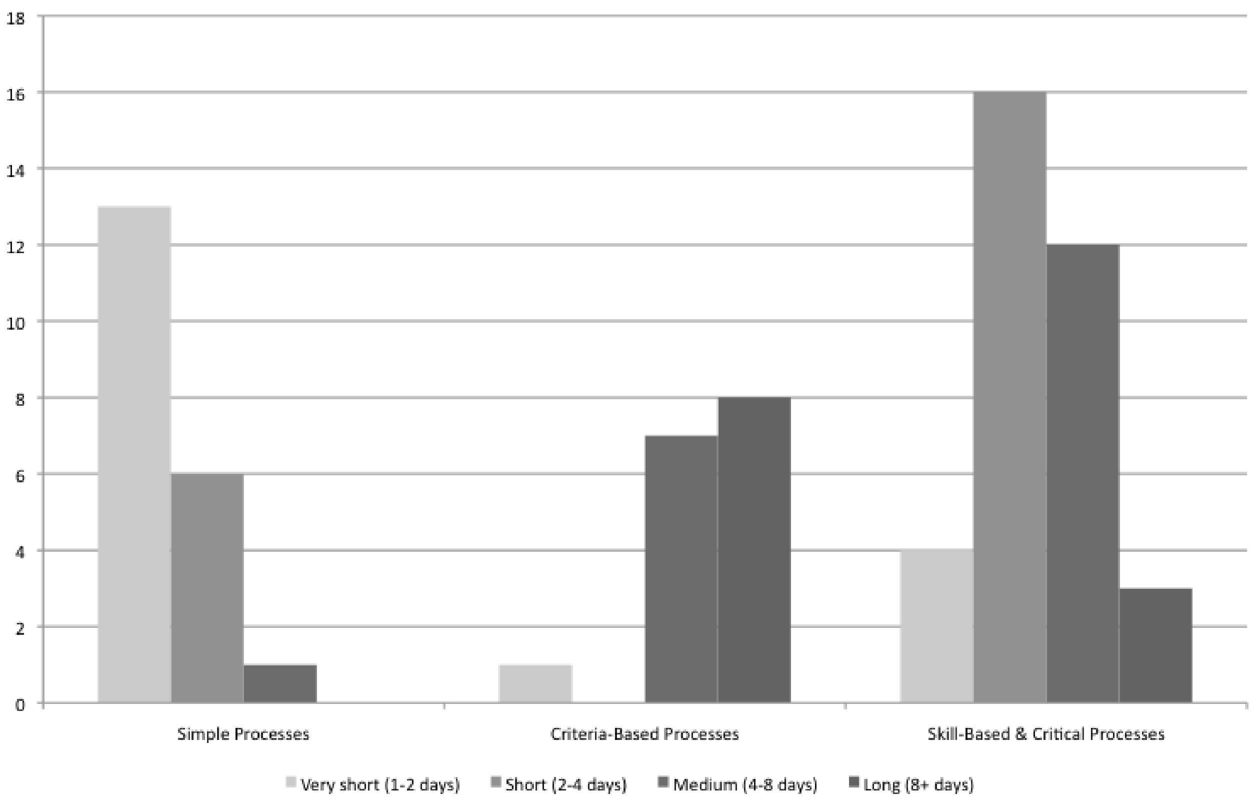

Figure 5.4. Histogram of processes by trainer categorization and training time.

time. Criteria-based processes take longer to train for – most fall into the long training time grouping (8+ days). The skill categorization has the most diverse grouping of different training times, the majority of which fall into the short grouping with the next largest contingent being the medium-length training time.

5.2.5.2 Training Categorization and Engineer Difficulty Rankings

Engineer rankings and training categorization have a clear-cut match as shown in Figure 5.5. Trainer-categorized simple processes have a high concentration of engineer ranked simple

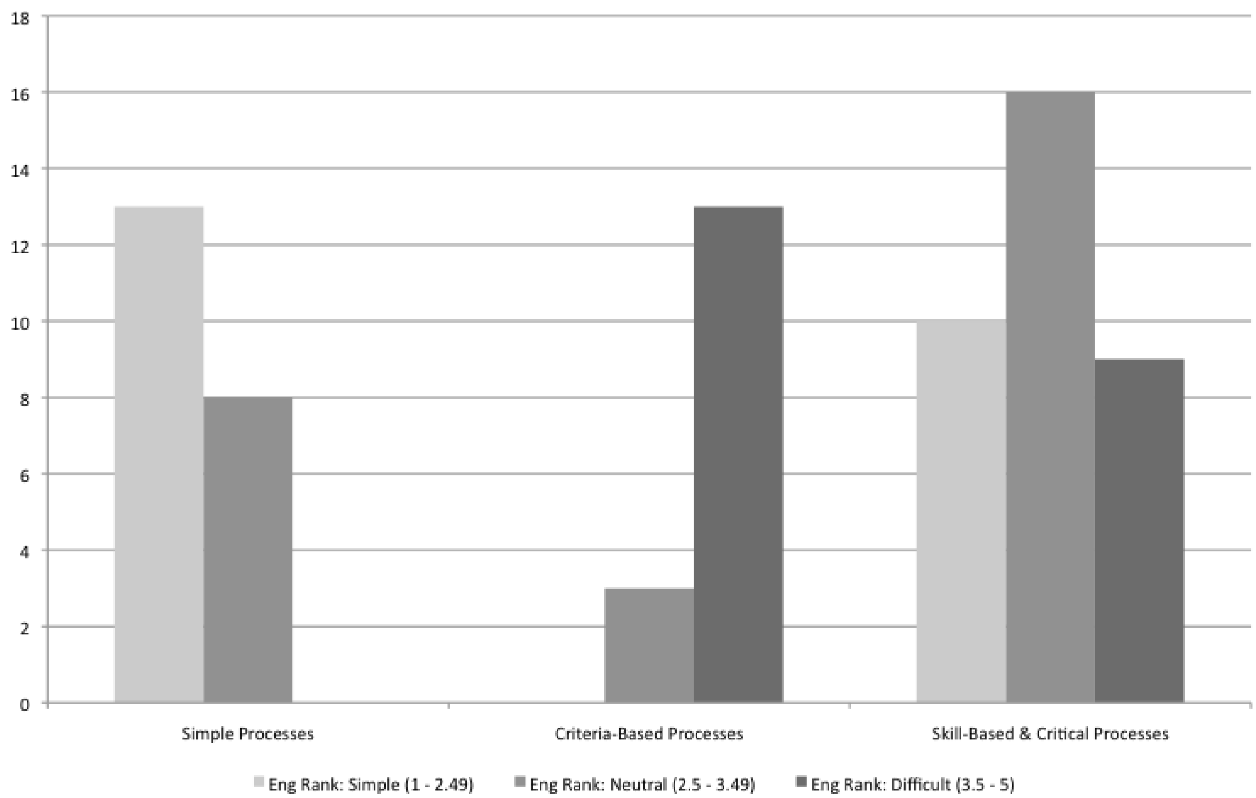

Figure 5.5. Histogram of processes by trainer categorization and engineer ranking.

processes with some neutral processes and no engineer-ranked difficult processes. Criteria-based processes have a high concentration of engineer-ranked difficult processes with some neutral processes and no simple processes. Skill-based processes are primarily ranked by engineers to be neutral with simple and difficult ranked processes coming in at about equal concentrations.

5.2.5.3 Engineer Difficulty Rankings and Training Time

Engineer rankings and training times also map to each other nicely, as shown in Figure 5.6. Processes with a difficult engineer ranking correspond to processes with a long training time.

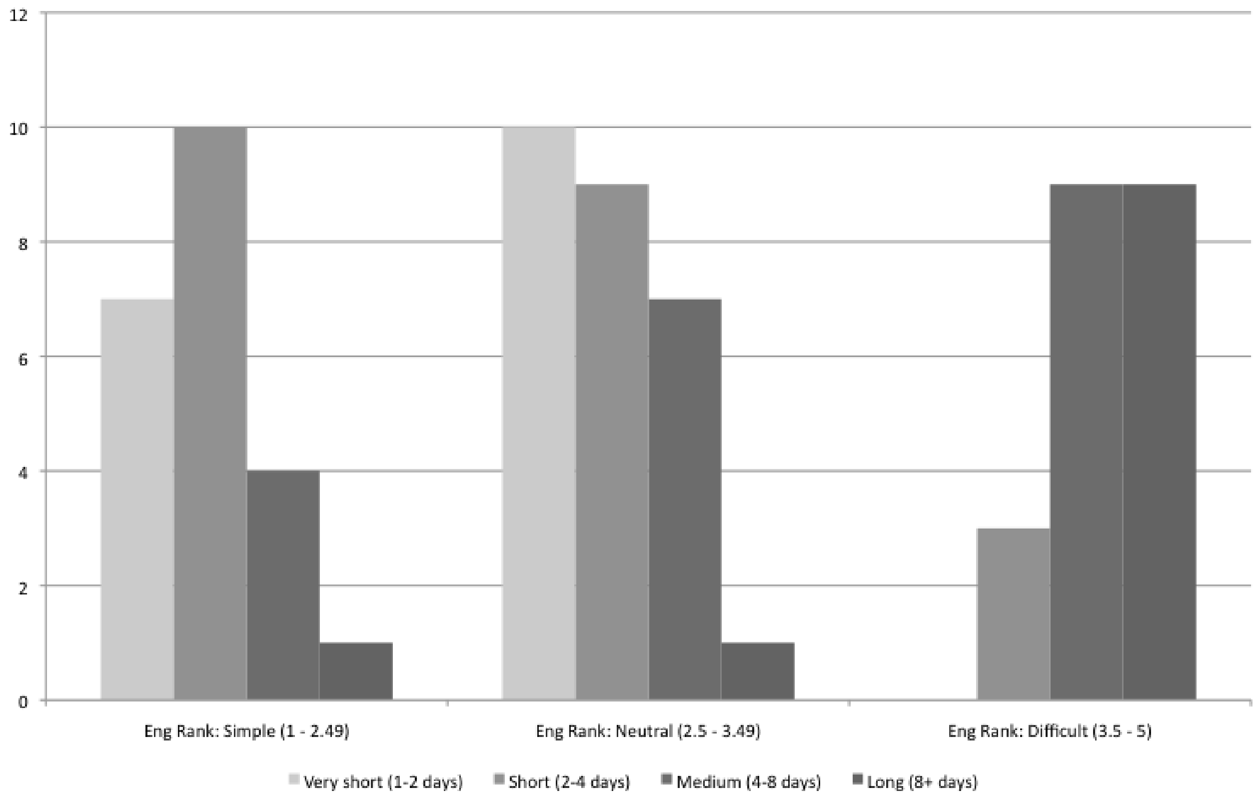

Figure 5.6. Histogram of processes by engineer rank and training time.

Engineer-ranked simple processes primarily take short training times. The neutral-ranked processes primarily correspond to very short training times, though there are a large number of processes which also take short and medium lengths of time to train.

In general, the three difficulty metrics give a consistent picture of difficulty perceptions of processes. Each measure gives a unique quantification to the difficulties of each process. In the next section we explore how these measures compare across each of our focus product groupings.

5.2.6 Process Difficulty Across Products

Recall the comparison of the evolution of focus products to generations and the statement that variation B is generally more complex than variation A. For the purpose of identifying trends across products, we will use the term complexity to capture the evolution of products from 1 through 4 where each consecutive product is more complex than the previous version and variation B is more complex than variation A. Complexity is a loaded word in the literature and we want to be careful with our definition here that we are capturing underlying technological advances and improved performance metrics of these products over time in our use and definition of complexity.

Table 5.7 shows process difficulty measures for each of our focus products. In general, as products become more complex the number of processes increases and the average training time per process decreases[3]. Trends across engineering rank are different for variation A than variation B: the average engineering rank per process increases for variation A and wavers for variation B. There are not clear trends across product complexity for the trainer categorization, though clearly the breakdown of types of process vary for each product. One final trend to note is the transition from products 1 and 2 of a split between very short and short training times as the largest process types to a concentration in the short training time processes for products 3 and 4.

[3]Notably, focus product 4B begins to reduce the number of process relative to 4A (and both 3A and B)

Table 5.7. Process difficulty metrics by focus product

Focus Product	1A	1B	2A	2B	3A	3B	4A	4B
Number of Processes	28	30	30	35	41	43	42	39
Engineer Rank								
Average Rank	2.76	2.89	2.82	3.08	2.89	2.89	2.90	2.77
Simple (1-2.49)	43%	37%	40%	23%	39%	35%	36%	38%
Medium (2.5-3.49)	29%	30%	27%	40%	32%	40%	38%	41%
Difficult (3.5-5)	29%	33%	33%	37%	27%	26%	26%	21%
Unknown	0%	0%	0%	0%	2%	0%	0%	0%
Training Time								
Average Training Time (days)	4.21	4.03	4.27	4.00	4.07	3.77	3.93	3.36
Very Short (<2 days)	33%	29%	20%	27%	16%	10%	15%	12%
Short (2-4 days)	23%	29%	40%	27%	47%	49%	51%	48%
Medium (4-8 days)	21%	23%	27%	23%	17%	14%	17%	15%
Long (>8 days)	18%	17%	17%	14%	17%	16%	17%	10%
Unknown	4%	3%	3%	3%	7%	7%	7%	8%
Trainer Categorization								
Skill	50%	43%	47%	54%	46%	47%	45%	49%
Criteria	18%	23%	23%	23%	24%	21%	24%	15%
Simple	29%	30%	27%	20%	22%	26%	24%	28%
Unknown	4%	3%	3%	3%	7%	7%	7%	8%

Finally, we can glean additional insights by extrapolating these by-product statistics over time. To do this we multiply the collected per-product difficulty statistics by the weekly per-product shipment data to create weekly measures of each of our difficulty rankings. This data certainly has limitations as it is reflecting a snapshot of perceptions of difficulty taken in 2011 onto data spanning from 2001-2011. However limited, though, this over-time process data does illustrate changes in processes and evolution of the overarching products over time.

From Figure 5.7 you can see the shift in processes toward a lower share of engineer-ranked simple processes in more recent years. This plot also shows how the share of difficult and

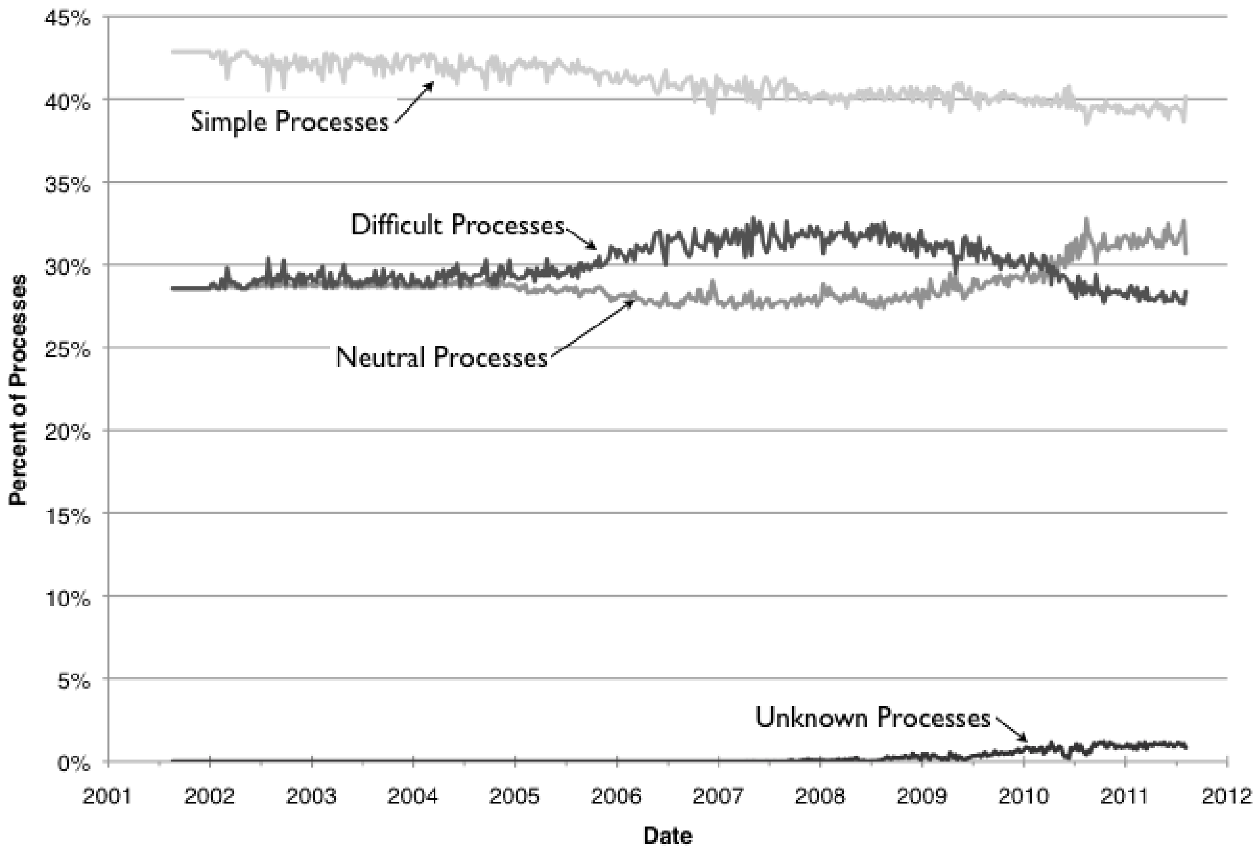

Figure 5.7. Share of processes over time by engineer rank.

neutral processes waver over time. On average though, as shown in Figure 5.9, processes have become more difficult over time.

When we extrapolate training times for each process over the time span of our shipment data, we see a dramatic change with the shares of training times. The change away from processes with a very short training time for focus products 3 and 4 and toward processes with a short training time becomes clear to see when you look at the shares over time by training time grouping in Figure 5.9. This shift also propagates through the average training time per process, Figure 5.10, which doesn't show a strong, discernible time trend.

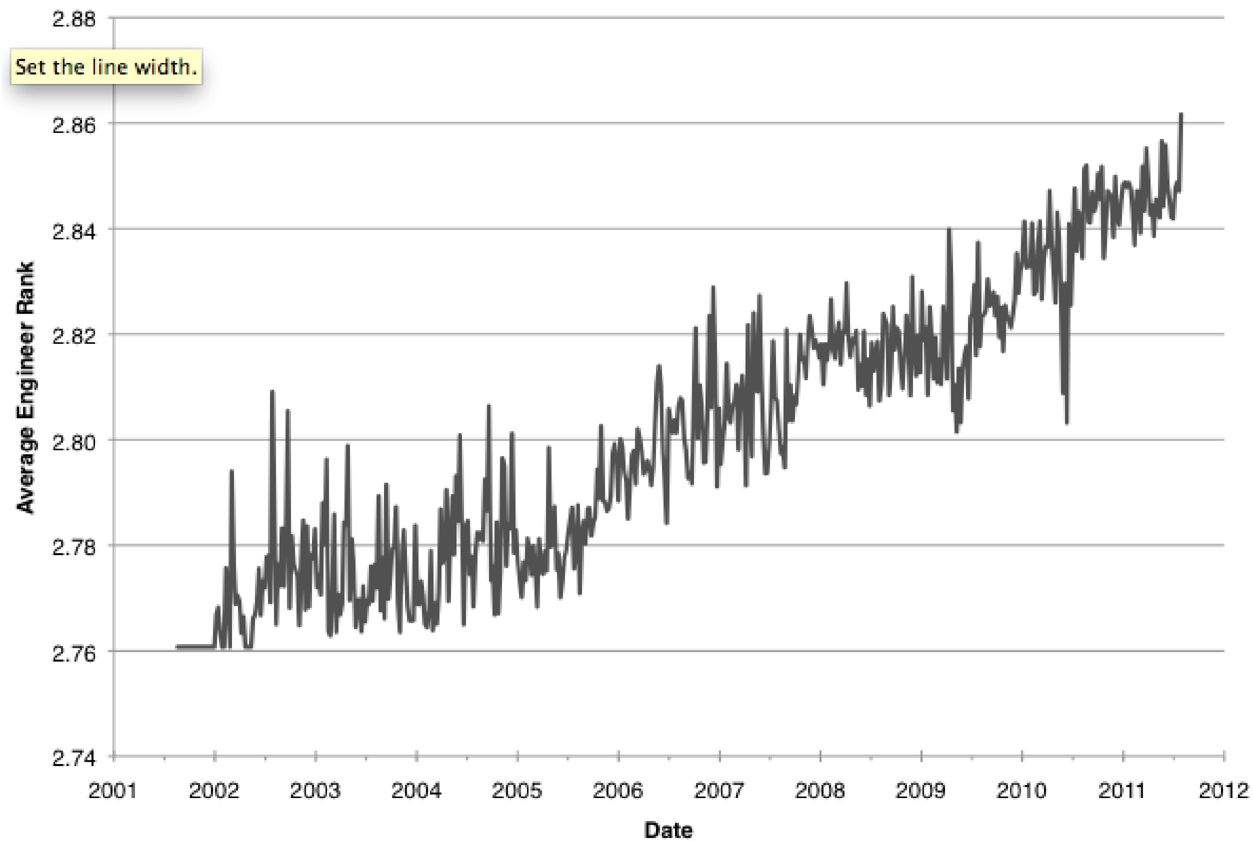

Figure 5.8. Average engineer rank per process over time.

Finally, we look at how the training categorization of processes over our time data looks in Figure 5.11. The most notable trend with this difficulty metric is the increase in criteria-based processes over time and corresponding decrease in skill-based and simple processes.

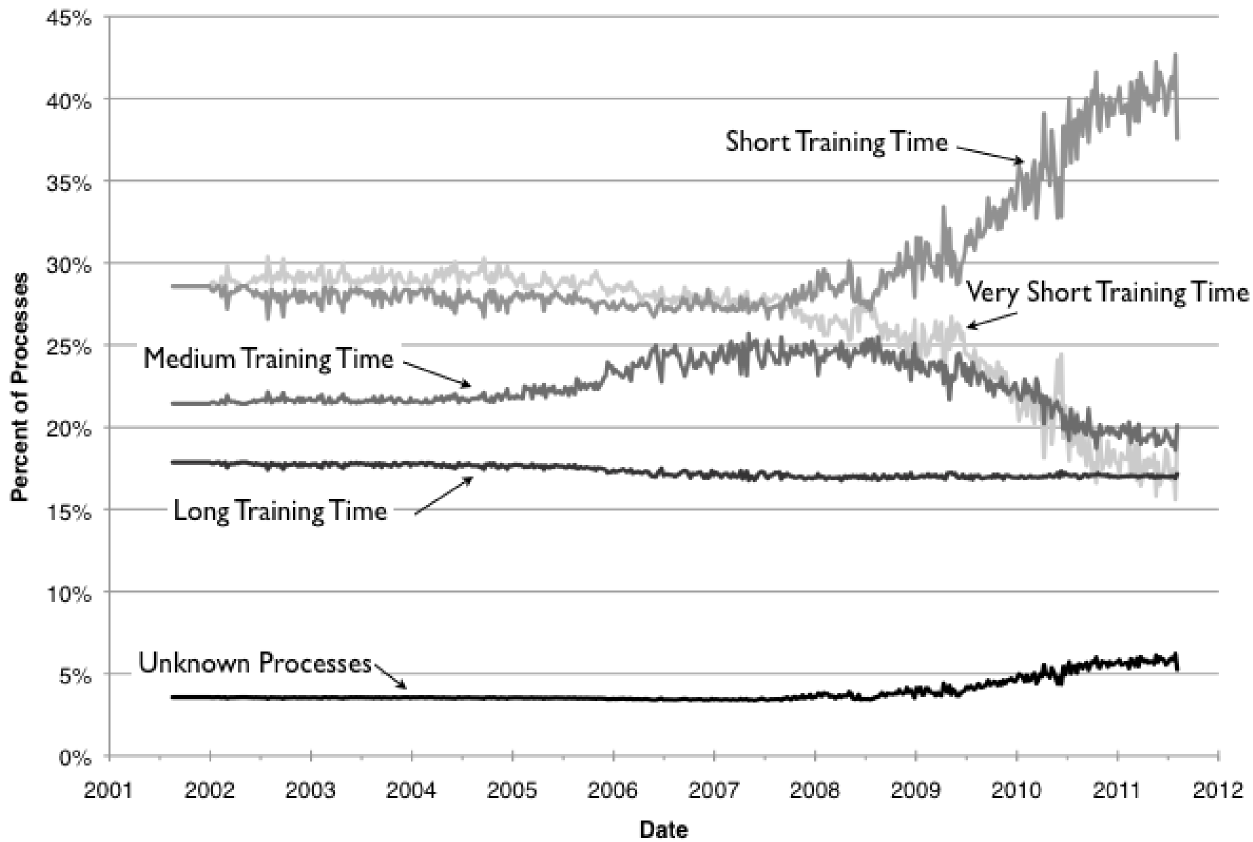

Figure 5.9. Share of processes over time by training time.

5.3 Conclusions: Process Commonality and Difficulty

We have collected a rich characterization of the processes of our focus products to try to gain insight into what elements of commonality and difficulty might be contributing to or deterring knowledge transfer. From the above discussion, we see elements of commonality across our focus products. There are, in fact, 12 process that are common across all focus products. That accounts for about a third of the process count for each product. Above those common-to-all processes, the older focus products (products 1 and 2) share a higher amount of common processes and the newer focus products (products 3 and 4) also share a higher amount of process commonality.

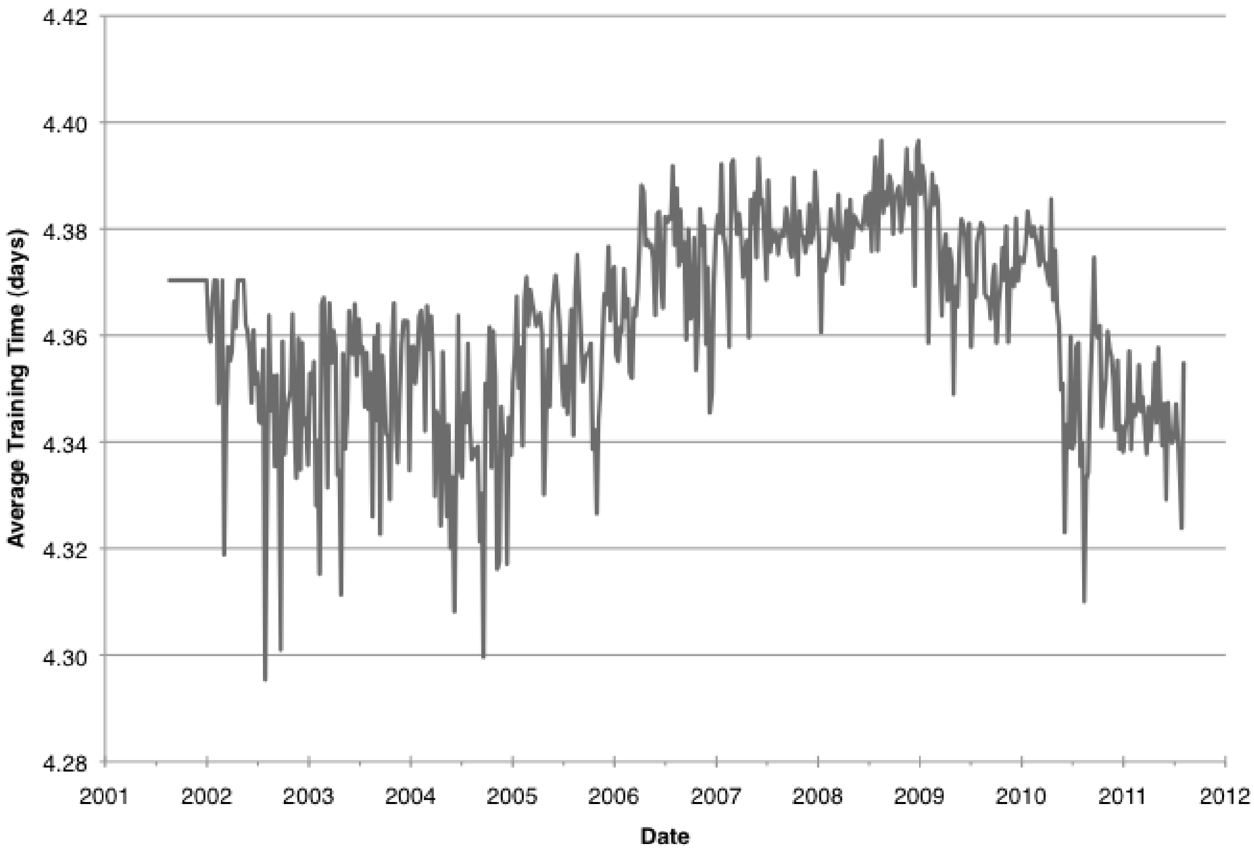

Figure 5.10. Average training time per process over time.

Table 5.8 shows a breakdown of the 12 common-to-all processes for each of the difficulty measures. These common processes span the range of each of the difficulty metrics. It should be noted that the unknown process for both training characteristics is a process owned by the quality department and is run by specially trained line workers and is outside the usual training process.

As the focus products have evolved through their generations and become more technologically complex, the plant has shifted towards more criteria-based processes which require longer training times and which are perceived by engineers to be more difficult processes. At the same time, these more complex products require fewer engineer-ranked simple processes

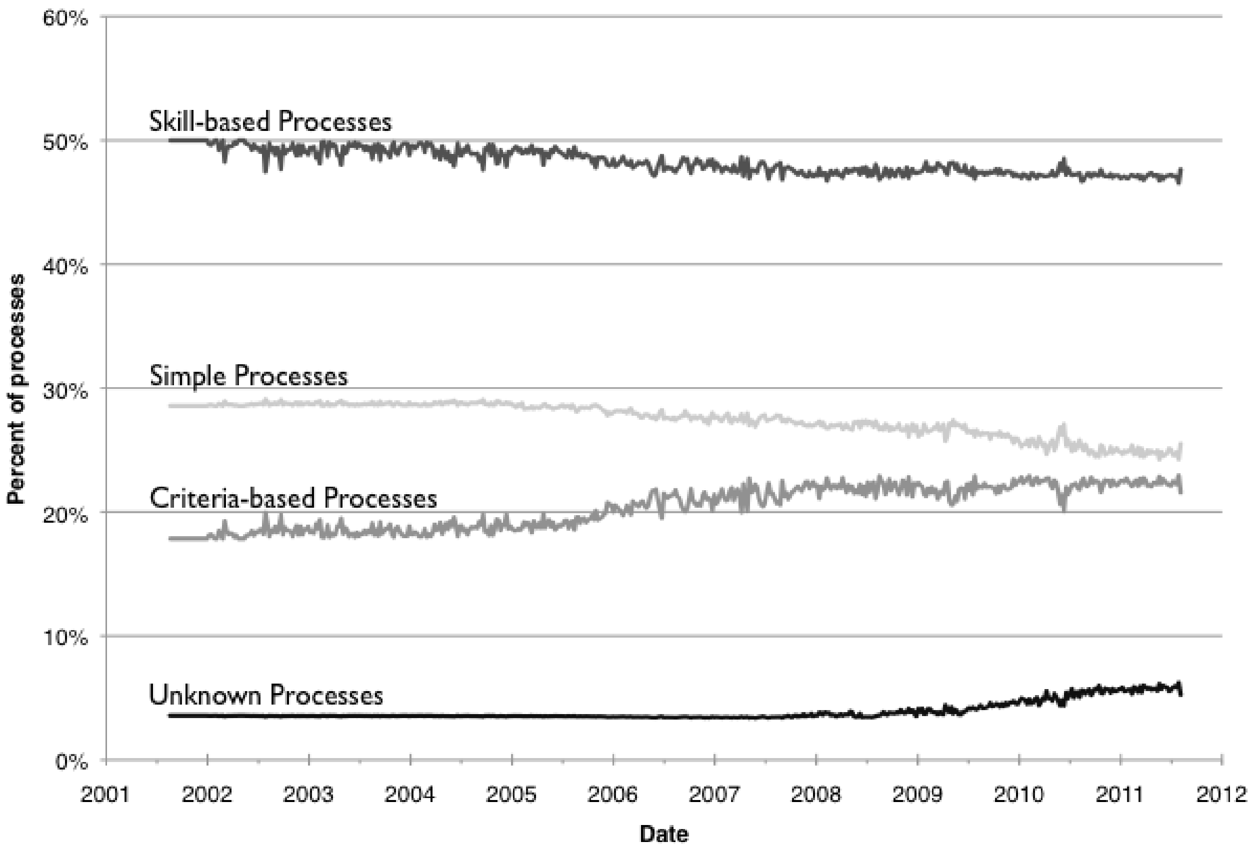

Figure 5.11. Share of processes over time by training categorization.

Table 5.8. Process Difficulty Metrics for Common Processes

Engineering Rank		Training Time		Training Categorization	
Simple	6	Very Short	2	Simple	3
Neutral	4	Short	2	Criteria	2
Difficult	2	Medium	5	Skill	6
		Long	2	Unknown	1
		Unknown	1		

and fewer very short training time processes.

The ability to add these measures back into our learning and knowledge transfer models can shed additional insights into the role that processes may play in the knowledge transfer process itself.

5.4 Additional Commonalities

There are two other potential repositories of knowledge or mechanisms for knowledge transfer we should consider: people and machinery. In the survey distributed to engineers, we asked questions about the commonality of machinery and of three types of employees across products.

We initially intended to ask these same questions of the trainers we would interview, but due to the limited number of trainers, language barriers, and time constraints we focused instead on the process questions in our focused interviews with trainers.

5.4.1 Person Commonality

Due to the small number of engineers able to take the survey for each stage of production, aggregating people commonality across three employee types (trainers, technicians, and engineers) and three production stages is a challenge. Many of the engineers were unaware or unable to answer about trainer and technician commonality across products. Additionally, in followup interviews with some of the engineers, it became apparent that some of the engineers filled in the commonality matrix based on intuition of expected commonality or overlap across products rather than fully knowing which engineers actually did overlap to other products.

5.4.2 Machine Commonality

The answers to the question about machinery commonality on the engineer survey gave us a general idea of how common machinery is across products, though we found similar complications as the person commonality question in how engineers were thinking about machine commonality across products. Some engineers only filled out the commonality for the specific product they worked on and with limited engineers per production stage, it is difficult to draw meaningful insights from the survey data.

Additionally, after discussions with the industrial engineering division and other maintenance divisions, we were able to get a more accurate count of machinery and understanding of machinery commonality from that quantitative data, detailed in Section 2.3.4.

Chapter 6

Organizational Learning and Knowledge Transfer Revisited: Process Difficulty and Minor Product Variations

In this chapter we look at the impact of adding the process difficulty and minor product variation measures detailed in Chapter 5 into the organizational learning and knowledge transfer models presented in Chapters 3 and 4. In Section 6.1, we investigate the impact of process difficulty variations within our generations of focus products on productivity. In Section 6.2, we explore the impact on productivity of producing the minor variations requested by customers of the focus products. In Section 6.3, we use run forecasting on several different scenarios of alternate product heterogeneity to test the relative impact of different product mix alterations. We then end in Section 6.4 with conclusions across these two elements of product mix.

6.1 Impact of Focus Product Process Difficulty

In the models in Chapters 3 and 4 we were unable to control for product or underlying process differences which can be important contributors to productivity. In this section we leverage the process information on engineering difficulty rankings, training times, and training categorizations detailed in Chapter 5. As detailed in Chapter 5, these process measures are certainly limited as they reflect a snapshot of difficulty perceptions taken in 2011 onto the 10 years of data available to our study. None the less, these measures do allow us to attempt to control for product differences in an important way. Sections 6.1.1 and 6.1.2 detail the impact of these focus-product process difficulty measures in the learning and knowledge transfer models, respectively.

6.1.1 Organizational Learning Model

The organizational learning model allows us to evaluate the role of organizational learning and product mix on the firm's productivity. In Chapter 3 we found 1) that the firm learned but that this rate of learning decreased over time, 2) that having increased heterogeneity of generations of the focus product being produced at the same time was helpful for firm productivity, and 3) that having an increased share of non-focus products being produced at once was harmful to productivity. Adding focus product process difficulty measures, as we do in this section, allows us to control for product differences across the focus products as captured by each of our three process difficulty measures.

Our results show that the organizational learning model results in Chapter 3 are robust. We sequentially added each of our process difficulty measures (average engineering rank, average training time, and share of trainer categorizations) to the organizational learning model, detailed in Chapter 3, to test for the impact of changes in process difficulty across the generations of focus products. These results are shown in Table 6.1. In each case the difficulty measure was itself not statistically significant and there are minimal changes in the magnitudes of the other coefficients in the model. The consistency of the core coefficients in the model show the robustness of the results presented in Chapter 3.

It is difficult to interpret a non-statistically significant result, a fact which is compounded by the types of measures we use for the process difficulty here — a one-time snapshot of difficulty projected backward over a 10 year period. One reason we may not be seeing an impact of these measures may be that our learning model doesn't differentiate between focus and non-focus products and our difficulty measures are solely for focus products. However, it is encouraging that our previous results from the learning model are robust to the inclusion of these measures.

Table 6.1. Estimation results: Instrumented foundational learning model with process difficulty measures.

Variable	Model 11	Model 12	Model 13	Model 14	Model 15
β_1, Experience $\ln(Q_{t-1})$	2.1366*** (0.5111)	2.4178*** (0.4477)	2.3561*** (0.4247)	2.4361*** (0.4239)	3.2208*** (0.6468)
β_2, Experience Sq. $(\ln(Q_{t-1}))^2$	-0.0546*** (0.0163)	-0.0640*** (0.0142)	-0.0610*** (0.0136)	-0.0639*** (0.0136)	-0.0893*** (0.0204)
β_3, Labor $\ln(L_t)$	0.4768*** (0.1475)	0.4639*** (0.1663)	0.3968** (0.1590)	0.4210*** (0.1517)	0.3393** (0.1635)
β_4, Share Non-focus $s_{Nonfocus,t}$	-1.8360*** (0.2986)	-1.8537*** (0.3216)	-1.8847*** (0.2998)	-1.8446*** (0.2983)	-1.8451*** (0.3070)
β_5, Focus Herf. $H_{Focus,t}$	-0.9022*** (0.3237)	-0.8125** (0.3434)	-0.9927*** (0.3664)	-0.9596*** (0.3470)	-0.8712*** (0.3101)
Eng. Rank Avg.	-2.4663 (1.8838)				
Train Time Avg.		0.6459 (1.1071)			
Share: Criteria			-3.7861 (3.2672)		
Share: Skill				5.1467 (4.7050)	
Share: Simple					-6.0427 (3.7345)
Obs.	461	461	461	461	461
R-squared	0.8803	0.8801	0.8802	0.8802	0.8804
Durbin-Watson	1.9891	1.9961	1.9972	1.9919	2.0164

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. Newey-West standard errors are used and are reported in parentheses. The constant term is omitted for firm confidentiality.

6.1.2 Knowledge Transfer Model

The organizational learning model allows us to evaluate the role of organizational learning and measures of product mix on the firm's productivity. The knowledge transfer model then allows us to look at second-order effects, that might help explain the increases and decreases in productivity associated with different products in the organizational learning model.

In Chapter 4 we found that the firm learned over time and that the firm was able to transfer knowledge across certain product types. Specifically, we found that knowledge transferred from older to newer generations of focus products; however, knowledge did not transfer from newer to older generations of products nor did knowledge transfer from focus products to non-focus products. We also found that our results on the impact of product mix from the learning model were robust in the knowledge transfer model – that increased focus product heterogeneity (having multiple generations of focus products being produced in the facility at once) was helpful for firm productivity and that increased shares of non-focus products were harmful to productivity. Adding focus product process difficulty measures to the knowledge transfer model, as we do in this section, will allow us to now control for differences in process difficulty across the focus products as captured by our three process difficulty measures.

The results from including our difficulty measures in the knowledge transfer model are shown in Table 6.2. The knowledge transfer model allows for more differentiation between focus and non-focus products (through the knowledge term, K_{it}) than the learning model, which may contribute to why we see impact from our process difficulty measures in the knowledge transfer model and not in the learning model.

In general, we see that our core results on knowledge transfer from Chapter 4 are robust to the inclusion of our process-based difficulty measures. We see that the firm is learning from its aggregate knowledge base[1], that knowledge transfers forward from older to newer

[1] Recall that the definition of the knowledge base, K_t, is defined as the aggregate knowledge across all prod-

Table 6.2. Estimation results: Knowledge transfer model with process difficulty measures.

Variable	Model 16	Model 17	Model 18	Model 19	Model 20
Transfer: Non-focus→Focus	-2.4273***	-3.7100***	-2.5079***	-2.5386***	-2.4971***
$\gamma_{NonFocus2Focus}$	(0.3731)	(0.4883)	(0.3390)	(0.4001)	(0.3521)
Transfer: Older→Newer Focus	1.5851***	1.1185***	1.8931***	1.5269***	1.3123***
$\gamma_{Old2New}$	(0.5790)	(0.3547)	(0.6097)	(0.5187)	(0.5090)
β_1, Knowledge	0.3450***	0.3296***	0.3751***	0.3598***	0.3334***
$\ln(K_{t-1})$	(0.0494)	(0.0386)	(0.0501)	(0.0495)	(0.0508)
β_3, Labor	0.4656***	0.3908***	0.3102***	0.3257***	0.4059***
$\ln(L_t)$	(0.1227)	(0.1281)	(0.1151)	(0.1177)	(0.1428)
β_4, Share Non-focus	-2.0333***	-2.1179***	-2.2044***	-2.1691***	-2.2096***
$s_{Nonfocus,t}$	(0.2199)	(0.2177)	(0.1998)	(0.2151)	(0.1890)
β_5, Focus Herf.	-0.6468**	-0.6059**	-0.6478**	-0.6229**	-0.6699**
$H_{Focus,t}$	(0.2560)	(0.2377)	(0.2595)	(0.2543)	(0.2607)
Eng. Rank Avg.	-4.1299**				
	(1.6176)				
Train Time Avg.		0.7156			
		(0.9918)			
Share: Criteria			-6.2296**		
			(2.8324)		
Share: Skill				6.3593*	
				(3.2954)	
Share: Simple					3.4222
					(3.7264)
Obs.	461	461	461	461	461
R^2	0.8530	0.8523	0.8529	0.8519	0.8521
Durbin-Watson	1.9630	1.9580	1.9825	1.9680	1.9725

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. The constant term is omitted for firm confidentiality.

generations of focus products, that knowledge does not transfer from non-focus to focus products, and that non-focus products are harmful to the knowledge base. Additionally,

uct types ($K_t = \sum_i s_{it} K_{it}$) where each product-specfic knowledge base, K_{it}, is defined as it past cumulative production plus some portion, γ, of past production of all other product types ($K_i = Q_{it} + \gamma_i (Q_t - Q_{it})$).

as with all prior iterations of the learning and knowledge transfer models, we see that an increase in the heterogeneity of focus products on the line is beneficial for productivity and that an increase in the share of non-focus products is harmful to current period productivity.

In the case of the knowledge transfer model, however, adding in our three process difficulty measures offers additional insights. We see that the engineering rank coefficient and some of the share of trainer-based process-categorization coefficients[2] are statistically significant in models 16 and 18–20. We do not see significance on the training time variable in model 17. The following paragraphs detail the interpretation of each of these process-difficulty variables and their impact on the knowledge transfer model.

Training time, model 17, is a tricky measure because it doesn't necessarily capture the difficulty of a process once workers are beyond the learning curve for the given process. (In contrast, the other measures [engineering process difficulty rank and training process categorizations] offer measures of everyday on-the-line performance.) Training time is a measure of the time for an average individual to become proficient at a given process. Additionally, as the production processes have evolved, some of the firm's learning and process difficulty has been codified in the machinery or tooling rather than in the steps an individual line worker would have to perform. Given these complications with the training time measure, it is not surprising that we do not see significance on the measure itself.

When we include engineering rank and share of process-categorization variables, in models 16 and 18–20, we see an increase in the magnitude of the forward transfer coefficient,

[2]The three categories of these trainer-based process categorization variables are simple processes, criteria-based processes, and skill-based processes. Section 5.2.4 details of each of these process types.

$\gamma_{Old2New}$, compared to the knowledge transfer model 9, presented in Section 4.3. These results underscore the robustness of our finding that the firm is able to effectively transfer knowledge forward from older to newer generations of focus products. Indeed, these results suggest that the forward transfer of knowledge may be greater than previously estimated.

We see, in model 16, that the coefficient on the engineering process difficulty term is negative and statistically significant at the 5% level, which means that as the average difficulty of processes in the facility increases, productivity decreases. This result validates the legitimacy of our choice of model as well as of this difficulty measure, as it is the result one would expect when controlling for difficulty.

In models 18–20 we see that some of our training process categorization share variables are significant and with the addition of each of the training process categorization variables our core results do not change.

Criteria-based processes are processes which require a line worker to visually inspect a product or perform a set task based on established criteria. In model 18 we see that an increase in the share of these processes in the facility decreases current-period productivity. This coefficient is statistically significant at the 5% level. This effect makes sense as criteria-based processes are the most labor-intensive processes so we would expect they would negatively impact current period productivity[3]. We also observe that the coefficient on forward transfer from older to newer generations of focus products is highest when we account for the portion of criteria-based processes. Criteria based processes were listed by engineers as

[3]We also see the labor coefficient is also at its lowest value in model 18 when we include the share of criteria-based processes.

the most difficult and by trainers as taking the longest time to train line workers. When we control for the difficulty involved in criteria-based processes (such as visual inspections), we see the firm is able to even more effectively learn from and transfer knowledge to new generations of products than previously estimated with the knowledge transfer model.

Skill-based processes are processes which require a developed skill for a line worker to perform the task. As can be seen in model 19, an increase in the share of skill-based processes in the facility has a positive effect on current-period productivity, although this coefficient is only significant at the 10% level. Given that skill-based processes require specific training, it is a bit surprising that an increase in these types of processes would have a positive impact. Notably, however, six of the twelve processes common to all focus products across the generations are skill-based, which may suggest that skill-based processes have more of an established baseline across all products and thus are less impacted by week-to-week changes. Another explanation may be that the share of skill-based processes has little impact on productivity in and of itself, but may be picking up the inverse of the impact of criteria-based processes as each of these variables is a share of total number of processes. In particular, when we include both of these share variables, we see they have an overall negative impact on productivity and are jointly-significant, but are not individually significant. This indicates that the shift in process composition over time is important for the model and that overall an increase in either skill-based or criteria-based process is harmful to productivity, but that these shares are linked and it is perhaps difficult to separate their impact.

Finally, simple processes are straightforward and do not require a special skill or set of criteria. As can be seen in model 20, the share of simple processes in the facility do not have a statistically significant effect on current period productivity. While a non-statistically significant results is hard to interpret, this indicates that the simple processes likely have little impact on current period productivity, which an engineer or manager would hope from the most simple and straight-forward processes.

The different coefficients and levels of statistical significance of our three process measures speak to the importance of the different aspects of process difficulty captured by each of the measures. Training time captures the average learning curve for individual line workers for each process (as perceived by the trainers). Changes in the composition of processes on the line weighted by training times does not impact firm productivity. This result might be interpreted as indicating that training is being successfully achieved offline, and thus not affecting activities on the line themselves. If, however, we instead look at the composition of focus-product processes based on trainer categorizations of simple, skill-based, and criteria-based processes, we see that the shift in the share of criteria-based processes has an impact on firm productivity, specifically that having more criteria-based processes in the facility decreases productivity. Finally, we see that engineer-rankings of process difficulty also capture shifts in the processes over time affect productivity. Here we find that increases in average process difficulty, as ranked by the engineers, decreases firm productivity.

6.2 Impact of Minor Product Variations: Leveraging Part Number Data

In both the organizational learning and knowledge transfer models we found that an increased heterogeneity of different generations of the focus product on the production line had a positive impact on productivity. In this section, we dig further into the impact of product variation on the line by leveraging the data we have on unique part numbers. Our focus firm works with a multitude of customers, many of whom have specific product requirements which range from minor differences, such as a different label orientation, to major differences, such as different test specifications or additional tests required. These customer-specific products are captured with different part numbers. These part numbers may be produced in the facility for a long period of time or may be one-time orders. This additional variation within our focus and non-focus product groupings is important to consider within our models.

While we defined our Herfindahl Index so as to capture a change in high-level product-grouping concentrations on the line (generations of the focus product and combined non-focus products), a measure utilizing the part numbers will capture how much variation within those major product groupings the production line sees. To accomplish this, I created a measure of minor product variations intended to meet customer specifications equal to the total part numbers divided by the shipment volume. Part numbers per shipment volume gives a measure of how much product differentiation we see within our higher-level product groupings. Figure 6.1 shows a plot comparing this measure for focus products and non-focus products. As can be seen in Figure 6.1, the ratio of part numbers to shipment volume is much higher for the non-focus products than the focus products. One contributor to this is the number of "base products" upon which the firm can create customer-specific variations. Within the focus products, there are the five generations plus the A/B variation as the base products. The base products within the non-focus products include the 14 different groupings detailed in Section 5.1.1 which cover a wide range of different form factors. Sections 6.2.1 and 6.2.2 detail the impact of the part number variables in our learning and knowledge transfer models, respectively.

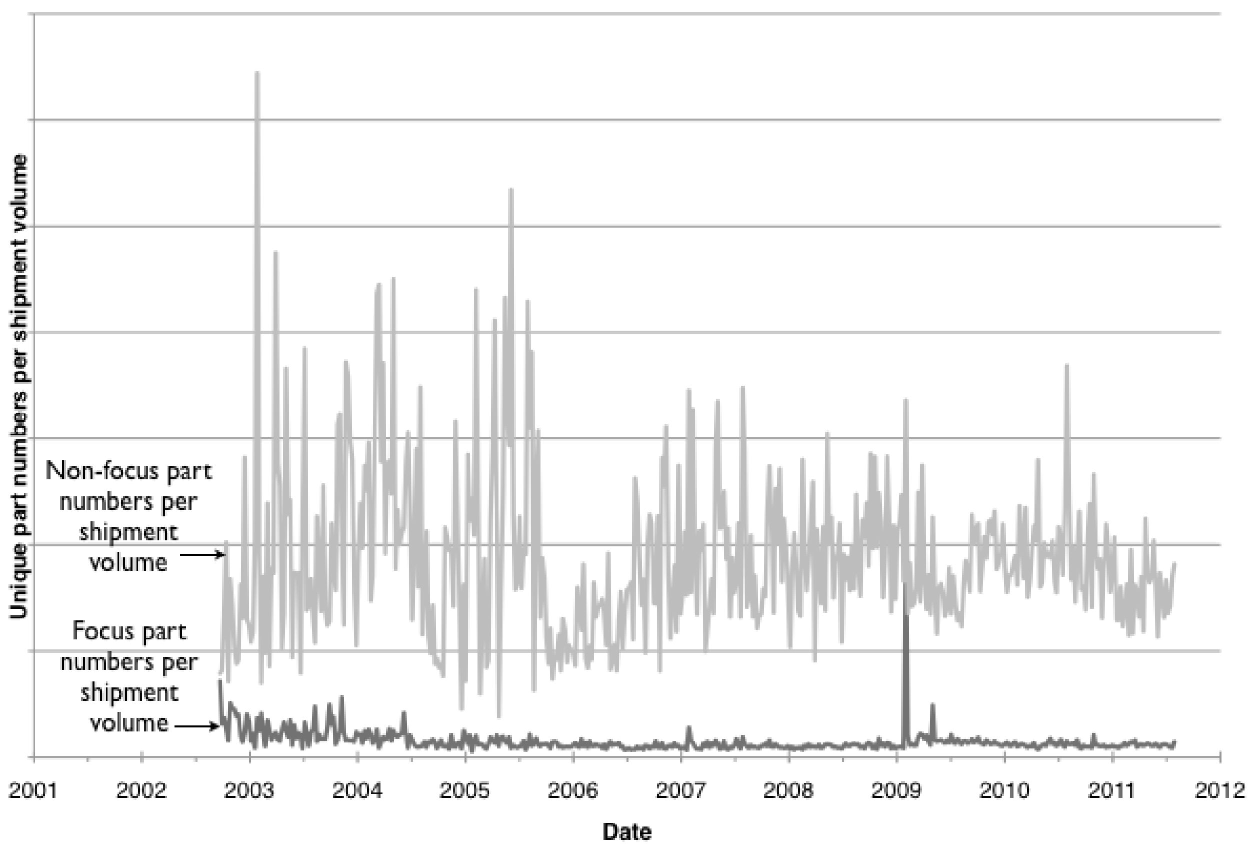

Figure 6.1. Unique part numbers per shipment volume for focus and non-focus product groupings.

6.2.1 Organizational Learning Model

We added the measures for part numbers per volume for both focus and non-focus products to the organizational learning model detailed in Chapter 3. Table 6.3 shows the results of the learning model with the addition of these minor product variation measures. The part number variables are also instrumented in the learning model in a similar manner to the instrumentation of the Herfindahl Index to account for any endogeneity which may occur within the scheduling of product types during production and shipment on the production line[4].

In the previous learning models (shown in Chapter 3 and Section 6.1.1) we included both an experience and experience squared term. Including the experience squared term was the best fit for the model, which indicated that while the firm did learn, this rate of learning decreased over time. With the inclusion of the part numbers per volume measures we find that inclusion of only the experience term (and not the experience squared term) gives us the best model fit. We find, however, that when we include both experience and experience squared in model 21 the terms are jointly significant. An explanation for this result may be that when we account for the part number variation we no longer see the decrease in the rate of learning we observed in previous models. This finding suggests that, if anything, we were underestimating the learning rate in the prior models shown in Chapter 3 and Section 6.1.1.

A notable consequence of including the part number variables is that the share of non-

[4] We included 6 weeks of order lags as instruments, averaged in 2-week intervals, as 6 weeks is the average order fulfillment time for the firm. Results shown here include these instruments for the Herfindahl Index and part numbers per volume for focus and non-focus products.

Table 6.3. Estimation results: Learning model with part number per volume measures.

Variable	Model 21	Model 22	Model 23
Experience	0.5512	0.3185***	0.3178***
$\ln(Q_{t-1})$	(0.3877)	(0.0942)	(0.0942)
Experience Sq.	-0.0078		
$(\ln(Q_{t-1}))^2$	(.0132)		
Labor	0.2791***	0.2645***	0.2840***
$\ln(L_t)$	(0.0779)	(0.0709)	(0.0787)
Share Non-focus	-0.6800	-0.8066	-0.7772
$s_{Nonfocus,t}$	(0.9739)	(0.9463)	(0.9312)
Focus Herf.	-0.5146**	-0.4418**	-0.4730**
$H_{Focus,t}$	(0.2597)	(0.2164)	(0.2218)
Partnums/Vol Focus	-725.1697***	-726.5723***	-718.6730***
$PPV_{Focus,t}$	(216.2458)	(222.2643)	(223.4499)
Partnums/Vol Non-focus	-18.9177	-21.3842*	-20.8833*
$PPV_{Nonfocus,t}$	(12.5000)	(11.5009)	(11.5235)
Eng. Rank Avg.			-0.6321
			(1.1404)
Obs.	461	461	461
R-squared	0.9548	0.9551	0.9550
Durbin-Watson	1.9359	1.9373	1.9380

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. Newey-West standard errors are used and are reported in parentheses. The constant term is omitted for firm confidentiality.

focus products variable is no longer statistically significant. In our previous specifications of the learning model (models 1-6 in Chapter 3 and models 11-15 in Section 6.1.1) we found that increased shares of non-focus products were harmful to firm productivity. Yet, prior to including the part number variables we were unable to characterize the non-focus products in a more refined way than simply their share of total weekly shipment volume. With the inclusion of our measure for minor product variations we begin to see a more subtle picture emerge.

We see that the part numbers per volume variables are, generally, statistically significant, negative, and different in magnitude from each other. The non-focus part numbers per volume coefficient is not statistically significant in model 21, but when we shift to model 22 without the experience squared term we see the coefficient on the non-focus part numbers per volume move to the 10% statistical significance level. While this result is not strongly significant, it does suggest that the an increase in minor product variations within non-focus products leads to a decrease in current-period productivity.

The coefficient on the focus product part number per shipment volume measure is also negative, but it is more strongly statistically significant, specifically at the 1% level. Care needs to be taken in interpreting the relative magnitudes on the non-focus and focus part number per volume measures as the per-week values and changes in values are quite different – non-focus products see a much higher level of part number variation. If we look at the productivity elasticities of both focus and non-focus part number measures, we see that focus products have a part number per volume elasticity of -0.20 while our non-focus products have a part number per volume elasticity of -0.07. These elasticities show that a 1% increase in focus part numbers per unit volume has an adverse effect on productivity that is three times as large as a 1% increase in non-focus part numbers per unit volume.

Notably, we see that the focus product Herfindahl Index is still statistically significant and still negative which indicates that increased heterogeneity within the high-level focus product groupings continues in this model to be beneficial for productivity. Combining this result with the interpretation of the part number variables, we can conclude that minor product variation is harmful for current productivity and that these minor product variations have a separate effect than the Herfindahl Index. These results underscore the importance of distinguishing between different types of product "mix" on the production line. The Herfindahl Index captures changes in the relative concentration of different generations of the focus product on the line, and an increase in the number of generations on the line has a positive impact on productivity. In contrast, part numbers per volume captures minor variations within our major product groupings, and an increase in these customer-specified minor variations has a negative impact on current period productivity.

We next add the process difficulty measures to the above model, and find that they are not statistically significant. This lack of statistical significance on the process difficulty measures is consistent with the results we found for the process difficulty measures in the learning model (Section 6.1.1) and in the knowledge transfer model (Section 6.1.2). These results suggest that learning occurs and focus product mix is beneficial when we control for focus product process differences. That our results remain the same when controlling for process differences between generations of the focus products further supports the robustness of our results. We see that the engineer rank average coefficient is still negative in model 23 as it has been in all previous models. These results are consistent with model 11 in Section 6.1.1, where the engineer process difficulty ranking is not statistically significant but it is negative. Negative is the expected sign for the engineers' process difficulty ranking. Finding a negative sign is thus encouraging when evaluating the robustness of the overall results of the model.

To summarize, when we add minor product differences to meet customer specifications, we find that learning occurs throughout the entire period of our analysis and does not decrease over time. We see that increases in minor product differences are harmful to current period productivity, that the share of non-focus products on the line may not be as harmful to productivity as originally estimated, and that increased heterogeneity of generations of focus products on the line is still beneficial to productivity.

6.2.2 Knowledge Transfer Model

We next add the measures for minor product variations to meet customer specifications (part numbers per volume) for both focus and non-focus products to the knowledge transfer model detailed in Chapter 4. The results are shown in Table 6.4.

We see in model 24 that the knowledge base term, K_{t-1} is still positive and strongly statistically significant, showing that the firm is learning from its cumulative knowledge base. When we account for the part numbers per volume for both focus and non focus products we see that the transfer term on non-focus to focus products, $\gamma_{NonFocus2Focus}$, is no longer significant (recall it was significant and negative in previous models[5]). In previous models we could only account for share of non-focus products – an important, but limited measure. Now, with a measure comparing variety within both focus and non-focus products, we are able to incorporate more information about the non-focus products into our model. Controlling for minor product variations within non-focus products, we see that the non-focus products

[5]Previous models include Section 4.3 models 7–10 and Section 6.1.2 models 16-20.

Table 6.4. Estimation results: Knowledge transfer model with part number per volume measures.

Variable	Model 24	Model 25
Transfer: Non-focus→Focus	-0.8364	-0.8124
$\gamma_{NonFocus2Focus}$	(0.8434)	(0.8805)
Transfer: Older→Newer Focus	1.4906**	1.4994**
$\gamma_{Old2New}$	(0.6885)	(0.7062)
β_1, Knowledge	0.2497***	0.2500***
$\ln(K_{t-1})$	(0.0292)	(0.0292)
β_3, Labor	0.2882***	0.2901***
$\ln(L_t)$	(0.0751)	(0.0807)
β_4, Share Non-focus	-0.3871**	-0.3834*
$s_{Nonfocus,t}$	(0.1920)	(0.2086)
β_5, Focus Herf.	-0.5047***	-0.5052***
$H_{Focus,t}$	(0.1820)	(0.1834)
Partnums/Vol Focus	-817.9062***	-817.7654***
$PPV_{Focus,t}$	(23.9560)	(23.9492)
Partnums/Vol Non-focus	-21.3830***	-21.3672***
$PPV_{Nonfocus,t}$	(2.4142)	(2.4157)
Eng. Rank Avg.		-0.0645
		(1.0713)
Observations	461	461
R^2	0.9179	0.9180
Durbin-Watson	1.9273	1.9273

Note: *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively. The constant term is omitted for firm confidentiality.

may not be as harmful to the firm's knowledge base, measured as cumulative production experience per product plus transfer across products, as our previous models suggest. First, we see that the non-focus to focus knowledge transfer parameter, $\gamma_{NonFocus2Focus}$, is no longer harmful to the firm's long-term knowledge base. While the term is still negative, it is no longer statistically significant. This indicates that while production of non-focus products may harm current period productivity it does not necessarily also degrade the long-term knowledge retention of the firm. Second, we also see a decrease in the significance of the term representing the share of non-focus products in the facility. This result shows that current-period productivity is less impacted by an increased share of non-focus products than we had estimated in our previous models. This result adds depth to our understanding of the impact of non-focus products. It also highlights the robustness of our earlier finding than an increase in heterogeneity of generations of the focus product on the line has a positive impact on current period productivity, since the positive impact of focus product Herfindahl Index remains a strong and significant measure in the knowledge transfer model.

When comparing the results from controlling for minor product variations in the knowledge transfer model to the results from the knowledge transfer without controlling for minor product variations, we see an increase in the magnitude of the older to newer focus product transfer coefficient, $\gamma_{Old2New}$, which goes from 1.14 in model 9 (Section 4.3) to 1.49 in model 24. While the standard errors on each of these coefficients do not make this increase in magnitude statistically significant, this results suggests that our our previous findings on forward transfer may underestimate the total transfer occurring across newer generations of focus products.

In the knowledge transfer model, the coefficients on the part number per volume measures themselves are negative, highly statistically significant, and similar in magnitude to the coefficients in the learning model. This result suggests the same interpretation as in the learning model – specifically, that increased part number variation within the major product groupings (in other words an increase in minor product variations) is harmful for productivity.

As with the learning model, when we include the part number per volume measures for both focus and non-focus products we see a decreased impact of the term representing the share of non-focus products on the line, $\alpha_{Other,t}$. The coefficient on this share of non-focus products term reduces in magnitude from -2.25 in model 9 (Section 4.3) to -0.39 in model 24 and has also decreased in significance level from the 1% level in model 9 (Section 4.3) to the 5% level in model 24. This still indicates that we see a negative impact on productivity from increased share of non-focus products, but less so that when we do not control for the part number variation.

The Herfindahl Index is still highly statistically significant and negative adding to the robustness of the finding that increased variation within the high-level focus product groupings is helpful for productivity.

We then also add the process difficulty measures to our knowledge transfer model and find that they are not statistically significant. Notably, we did find some statistical significance of these variables previously in the knowledge transfer model without minor product variations, as presented in Section 6.1.2. We see in model 25 that the sign on the average engineer difficulty ranking variable is still negative (i.e. the same as model 16 in Section 6.1.2 without minor part number variations). This result is encouraging – in that it continues to suggest that our analysis is robust – despite the fact that the term is not statistically significant. Notably, when we control for engineer ranked process difficulty we see the significance level decrease on the share of non-focus products coefficient from the 5% level to the 10% level. This result highlights the sensitivity of the variable representing the share of non-focus products on the line to the addition of other measures such as process difficulty when we control for minor product variations. Overall, the results of the knowledge transfer model prove quite robust when we account for process difficulty.

6.3 Forecast Analysis

We can shed insight into the relative impact of changes in product mix composition on the line by simulating how the firm would have performed with alternate scenarios of product heterogeneity. Specifically, we look at changes in the extent of non-focus products on the production line (scenario 1), changes to the heterogeneity of generations of focus products on the production line (scenario 2) and changes in the amount of customer-specific part numbers on the production line (scenarios 3-4). Table 6.5 shows the details of each of the product mix scenarios. We can then predict how the firm would have performed in each of these scenarios over time by running a simulation after replacing the product mix variable(s) with the appropriately altered variable(s) for the given scenario. Section 6.3.1 details the simulation model and appropriate uncertainty analysis in interpreting these results. Section 6.3.2 presents the results of the forecast analysis for each scenario.

6.3.1 Forecast Simulation Selection

We calculate two different metrics for the impact of each of these product mix composition scenarios. The first metric is the change in total shipment volume, ΔQ, if the firm stays at

Table 6.5. Forecasting simulation scenarios

Scenario	Description
0	Baseline (Model with actual data)
1	All non-focus product production shifted to focus product production
2	Allow newer focus product generations to completely replace older focus product generations within one quarter
3	Reduce non-focus part numbers to 1 per form factor
4	Reduce focus part numbers to 2 per generation (1 each for type A and type B)

their actual weekly employed labor level, L_t. The second metric is the change in total labor requirement, ΔL , if the firm stays at their actual weekly shipment volume level, q_t. Each metric is forecasted separately.

We base our forecasts off of the specification of the learning model presenting in model 22, shown in Table 6.3, for both methods of prediction. Model 22 is the preferred specification of the learning model as we see the best model fit with the inclusion of the part number variables for both focus and non-focus products. We present results here from this specification of the learning model rather than the equivalent specification of the knowledge transfer model (model 24, Table 6.4) as these models give similar results and prediction interval analysis is more simple for the learning model.

For the change in shipment volume output, we simulate the predicted shipment volume using the following specification:

$$\begin{aligned} \ln(Q_t - Q_{t-1}) = \beta_0 + \beta_1 \ln(Q_{t-1}) + \beta_3 \ln(L_t) + \beta_4 s_{other,t} + \beta_5 H_{focus,t} \\ + \beta_6 PPV_{focus,t} + \beta_7 PPV_{nonfocus,t} + \epsilon_t \end{aligned} \tag{6.1}$$

We replace $\ln(q_t)$ in the original specification (equation 3.1 in Section 3.2) with the equivalent

$\ln(Q_t - Q_{t-1})$ to allow for a dynamic simulation.

We can run forecast simulations on this equation several ways. A static forecast predicts a one-step ahead estimate of $\ln(Q_t - Q_{t-1})$ using the actual values for the lagged variable, Q_{t-1}, rather than the forecasted values, thus we see very little change in this forecast and the 90%-confidence interval band is very tight as seen in Figure 6.2. The static forecast over-

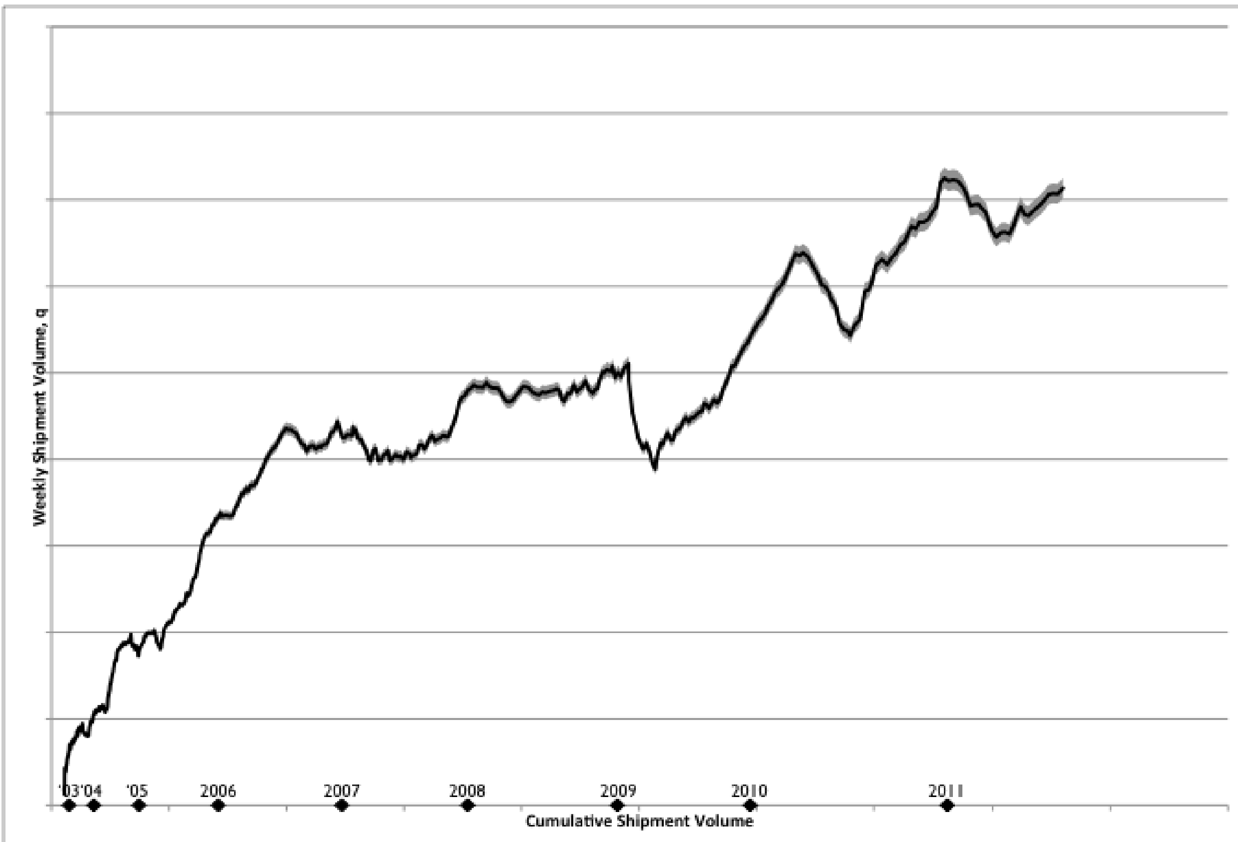

Figure 6.2. Static forecasting result. Shaded area indicates 90% confidence interval. Point estimates and confidence interval shown are quarterly averages.

states the certainty with which we can accurately predict shipment output in these alternate scenarios. A dynamic forecast will predict estimates for $\ln(Q_t - Q_{t-1})$ using the predicted values for the lagged variable, Q_{t-1}. In the dynamic forecast, we see error from each step

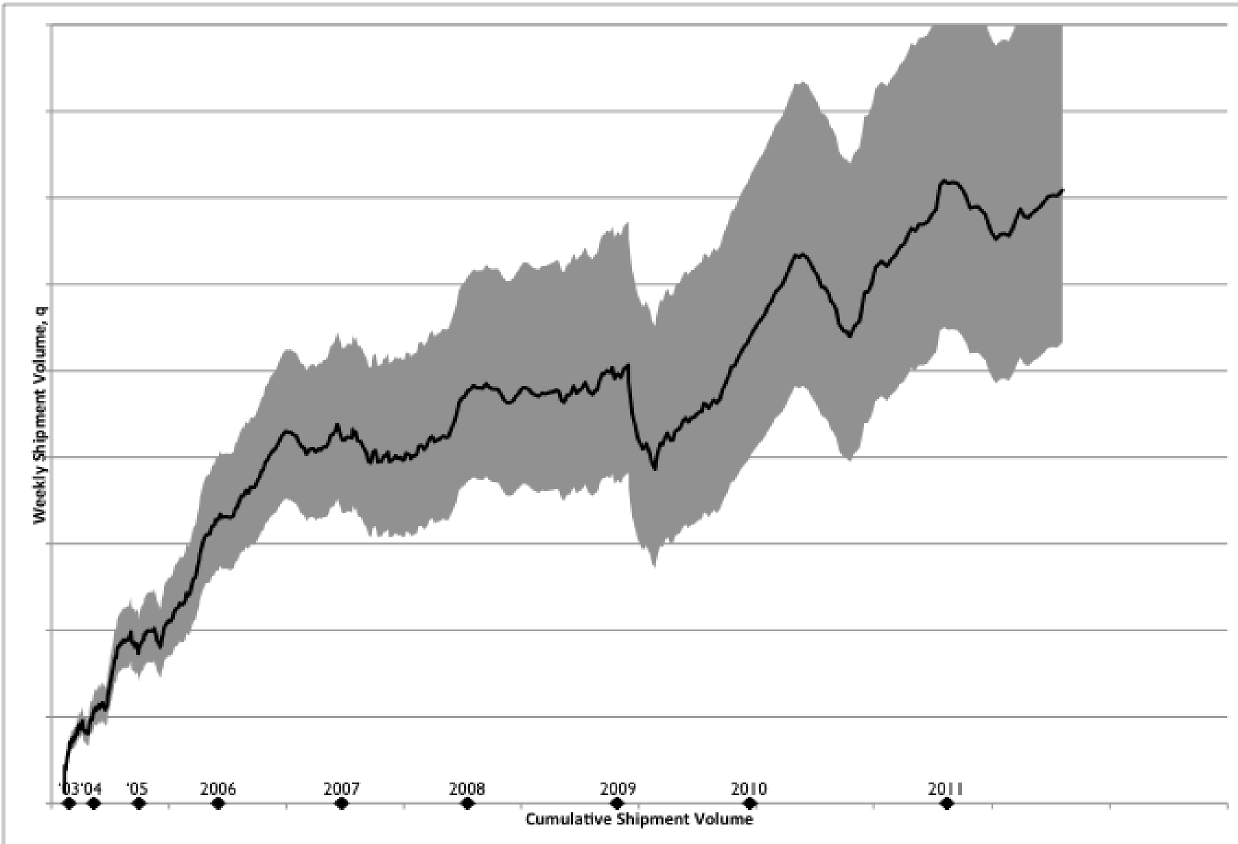

Figure 6.3. Dynamic forecasting result. Shaded area indicates 90% confidence interval. Point estimates and confidence interval shown are quarterly averages.

cumulate over the entire course of production for the facility (465 weekly observations, roughly 9 years) as we base all future estimates of q_t, and thus Q_t, on the initial shipment volume. Figure 6.3 shows the dynamic forecast with the 90% confidence interval of the prediction. The dynamic forecast dramatically understates the certainty with which we can accurately predict shipment output in these alternate scenarios, a common problem when using dynamic forecasts in time series data. A more reasonable dynamic prediction period is one quarter (13 weeks). The firm operates largely on quarterly sales and shipment goals so this is a natural prediction time period within the context of the firm. Thus, the third forecast method we

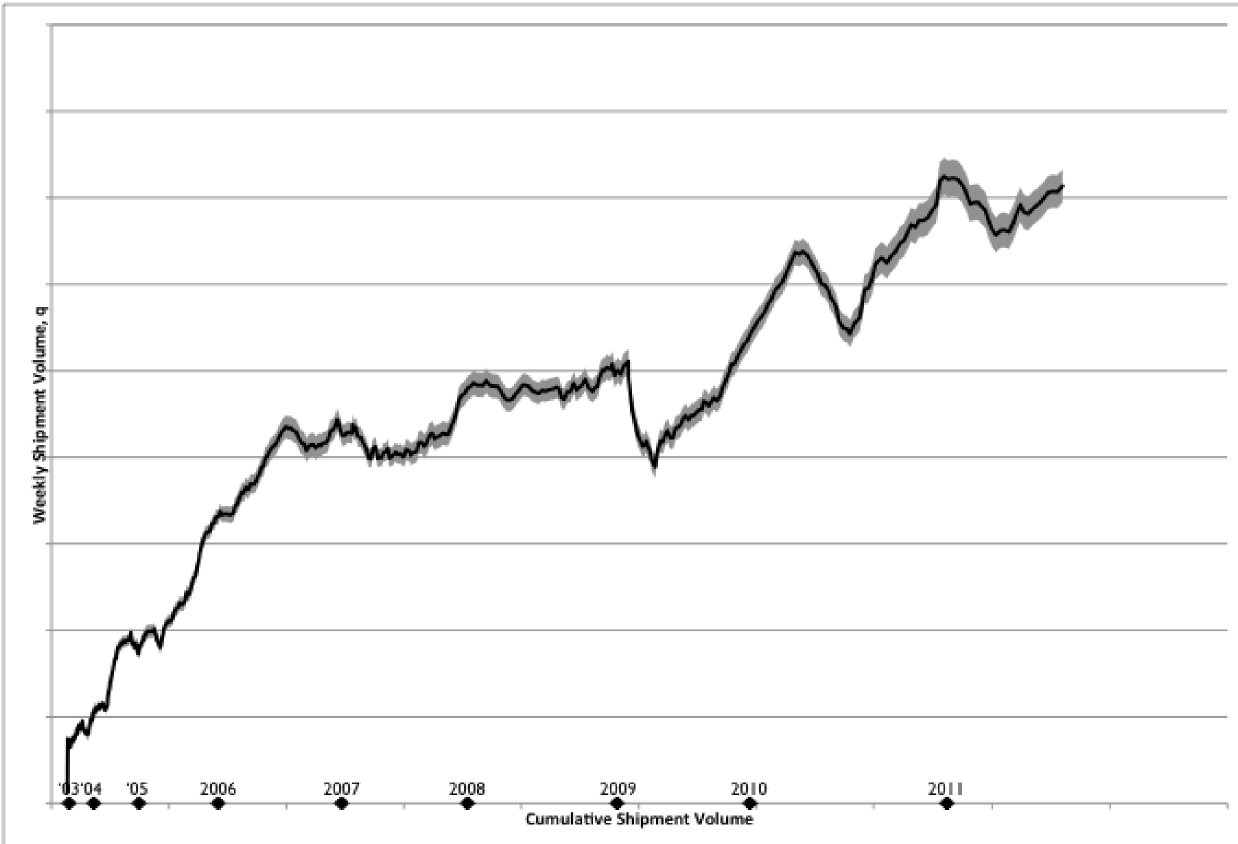

Figure 6.4. One quarter-ahead dynamic forecasting result. Shaded area indicates 90% confidence interval. Point estimates and confidence interval shown are quarterly averages.

use is a quarter-ahead-dynamic prediction. This method strikes the balance of allowing the lagged term, Q_{t-1}, to be dynamically estimated, but within a more reasonable prediction time frame. Figure 6.4 shows the dynamic forecast with the 90% confidence interval of the prediction. We use one quarter-ahead dynamic forecasting for all scenario results presented for ΔQ in Section 6.3.2.

For the change in labor input prediction, we calculate the predicted labor-requirement based on the following specification:

$$\ln(L_t) = \frac{1}{\beta_3}\left[\ln(q_t) - \beta_0 - \beta_1 \ln(Q_{t-1}) - \beta_4 s_{other,t} - \beta_5 H_{focus,t} \right. \\ \left. -\beta_6 PPV_{focus,t} - \beta_7 PPV_{nonfocus,t} - \epsilon_t\right] \tag{6.2}$$

We do not dynamically forecast this specification as we are concerned with the labor input at the actual weekly shipment volumes.

6.3.2 Forecast Simulation Results

Table 6.6 shows the quarter-ahead dynamic forecast outcomes for both the cumulative change in shipment volume output with the baseline employed labor input (ΔQ, $L_{baseline}$) and the cumulative change in labor with the baseline shipment volume output (ΔL, $q_{baseline}$) for each altered product mix scenario.

The percent change in shipment volume output with the baseline employed labor input, ΔQ, is given as

$$\Delta Q_{scenario} = \frac{Q_{scenario} - Q_{baseline}}{Q_{baseline}} \times 100\% \tag{6.3}$$

Similarly, the percent change in labor with the baseline shipment volume output, ΔL, is given as

$$\Delta L_{scenario} = \frac{\sum_{t=1}^{T} L_{t,scenario} - \sum_{t=1}^{T} L_{t,baseline}}{\sum_{t=1}^{T} L_{t,baseline}} \times 100\% \tag{6.4}$$

We see disproportionate results between the decrease in labor requirements and increase in shipment volumes in scenarios 1 and 3-4 and a similarly disproportionate increase in labor

Table 6.6. Forecasting simulation scenarios and outcomes.

Scenario	Description	ΔQ, $L_{baseline}$	ΔL, $q_{baseline}$
0	Baseline	– (-3%, 6%)[a]	–
1	All non-focus product production shifted to focus product production	27% (13%, 47%)	-57%
2	Allow newer focus product generations to completely replace older focus product generations within one quarter	-21% (-28%, -12%)	143%
3	Reduce non-focus part numbers to 1 part per form factor	16% (10%, 26%)	-40%
4	Reduce focus part numbers to 2 per generation (1 each for type A and type B)	66% (55%, 83%)	-82%

[a]90% confidence interval is shown in parentheses.

requirement and decrease in shipment volumes for scenario 2 due to the fact the firm sees diminishing marginal returns to labor with a labor coefficient of 0.26 in model 22.

Figures 6.5–6.8 show the quarter-ahead forecast results for decreasing the extent of non-focus products on the production line (scenario 1), reducing the heterogeneity of generations of focus products on the production line (scenario 2), and reducing the amount of customer-specific part numbers on the production line (scenarios 3-4), respectively.

6.4 Conclusions

From our survey work quantifying product and process differences we were able to extend our initial analyses of organizational learning and knowledge transfer in a multi-product manufacturing environment. In particular, we control for and test for the impact of several important additional elements on the production line: process difficulty and a more fine-

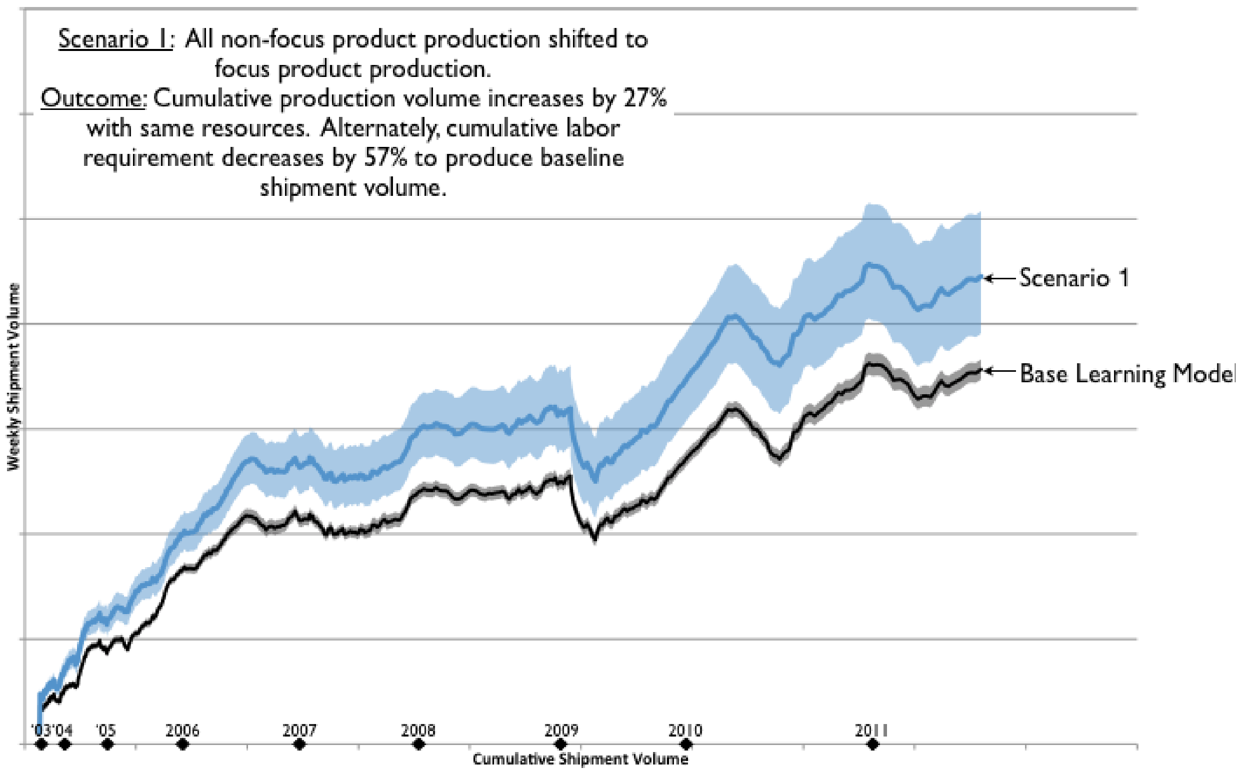

Figure 6.5. One quarter-ahead dynamic forecasting result for reducing share of non-focus products (scenario 1). Shaded area indicates 90% confidence interval. Point estimates and confidence interval shown are quarterly averages.

grained level of product variation (minor product variations on associated with meeting customer specifications on focus products and the broader range of non-focus products).

We find the results of our initial learning and knowledge transfer models to be overall robust while discovering additional insights across focus and non-focus products on the effects of process difficulty and mix on current-period productivity, learning, and knowledge transfer.

Organizational Learning Results: Overall we find the organizational learning model results to be robust. We find that the inclusion of focus-product process difficulty measures have no impact in the learning model, perhaps because the learning model does not distinguish

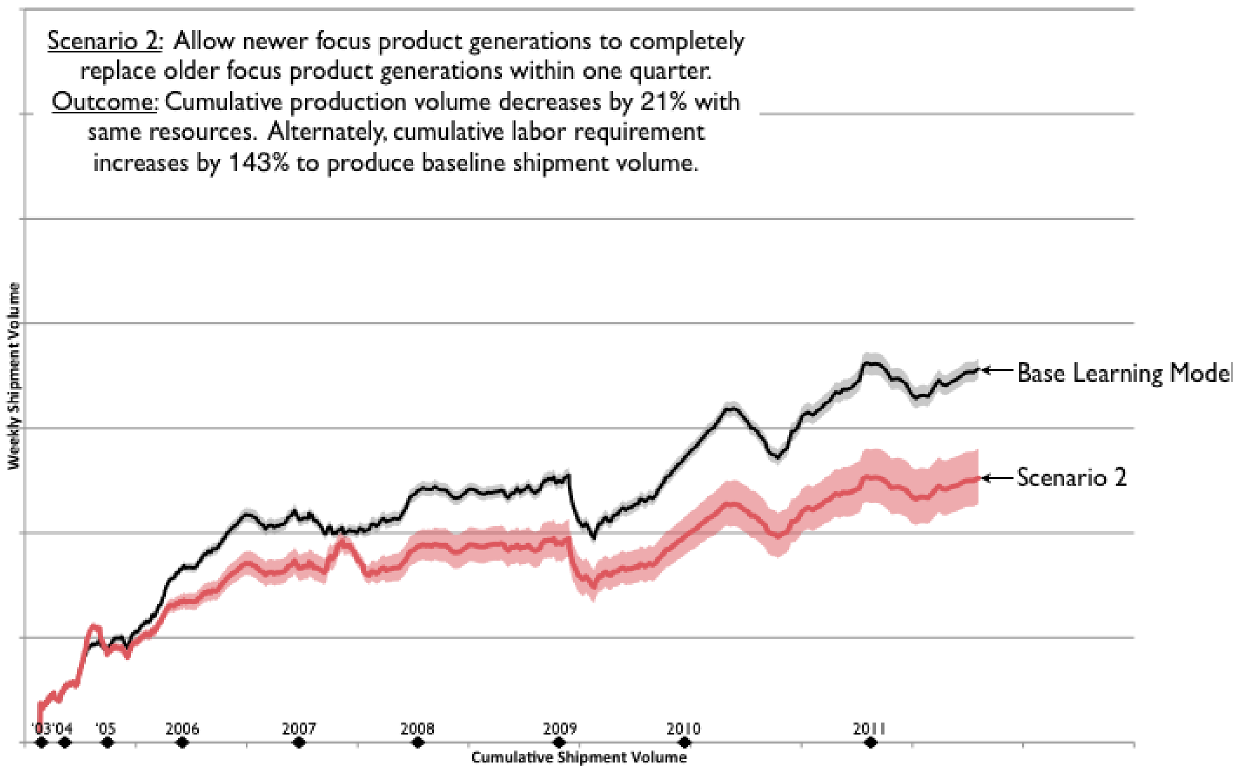

Figure 6.6. One quarter-ahead dynamic forecasting result for reducing heterogeneity of generations of focus products (scenario 2). Shaded area indicates 90% confidence interval. Point estimates and confidence interval shown are quarterly averages

between the focus and non-focus products. Importantly, however, the results of the learning model are robust to the inclusion of these measures. This robustness suggests that unobserved process difficulty is not likely to be driving our results.

When we include part number variation measures in the learning model we find that having an increased number of minor product variations on the line is harmful to current period productivity and that there is a difference in the magnitude of this impact between focus and non-focus products. Controlling for these minor product variations, we see that an increase in variation of major focus product groupings, measured by the Herfindahl Index, is still helpful for firm productivity.

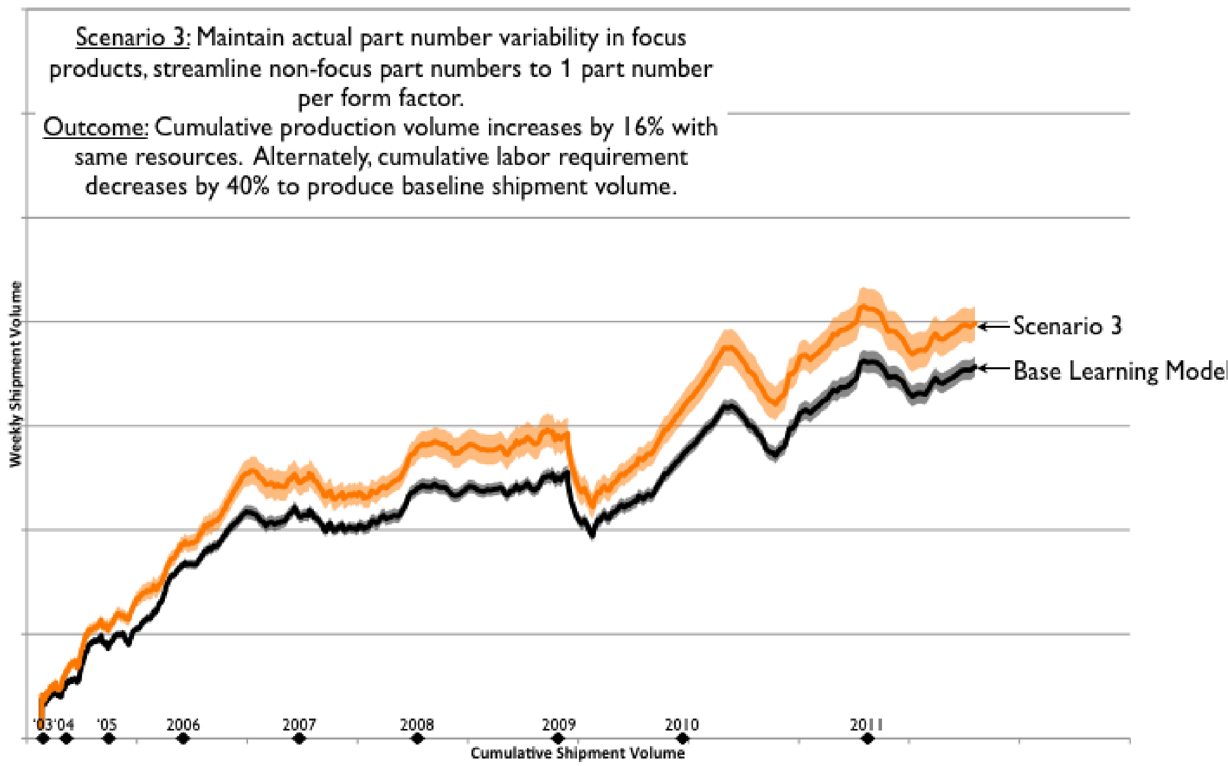

Figure 6.7. One quarter-ahead dynamic forecasting result for reducing non-focus part number variability (scenario 3). Shaded area indicates 90% confidence interval. Point estimates and confidence interval shown are quarterly averages

Knowledge Transfer Results: As with the learning model, we find the knowledge transfer model results are robust to the inclusion of process difficulty measures, however, most of the focus product process difficulty measures were significant in the knowledge transfer model while they were not in the learning model. We likely see more nuance from the focus-product process difficulty measures in the knowledge transfer model as this model allows for more detail across focus and non-focus products than the learning model. Controlling for process difficulty we see some increase in the transfer of knowledge forward across new generations of focus products, suggesting we may be underestimating this forward transfer in earlier models.

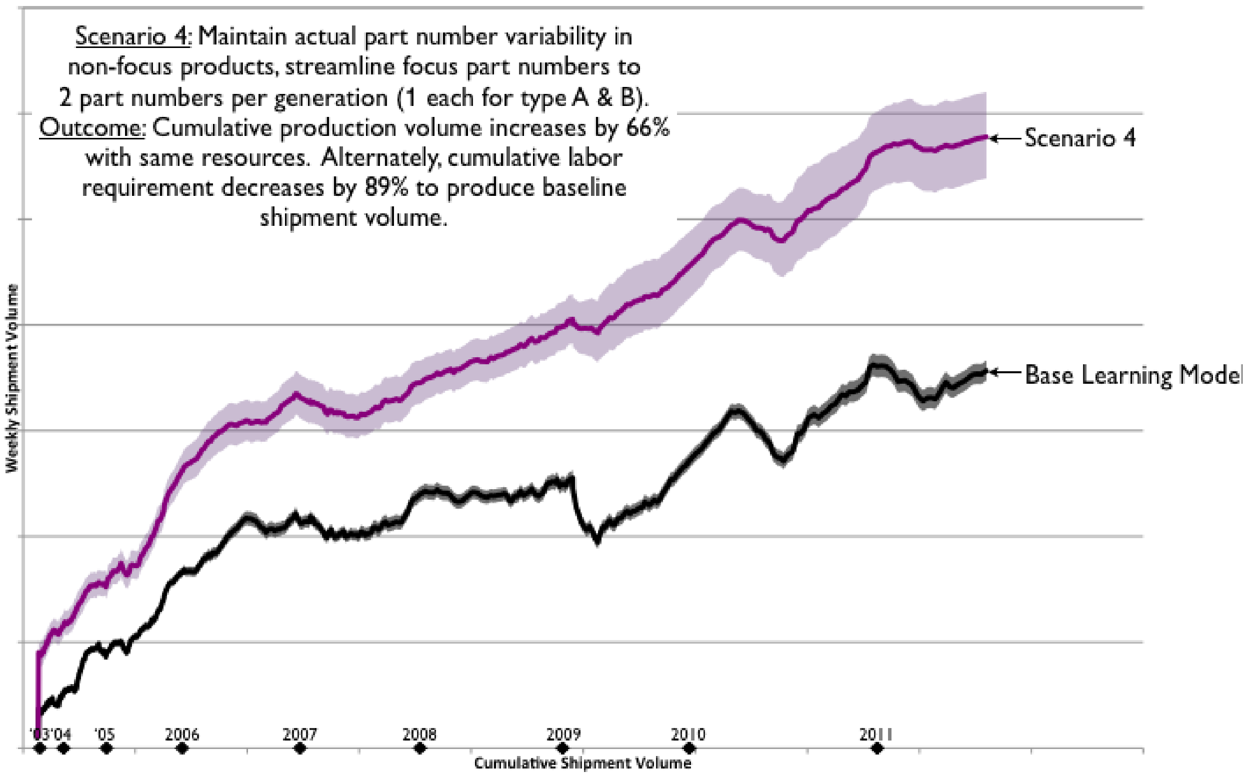

Figure 6.8. One quarter-ahead dynamic forecasting result for reducing focus part number variability (scenario 4). Shaded area indicates 90% confidence interval. Point estimates and confidence interval shown are quarterly averages

When we control for the part number variation in the knowledge transfer model we find our results to generally be robust, but there are a few important new insights. We continue to see a negative impact of an increased share of non-focus products on the line for current period productivity, but we no longer see harm to the firm's cumulative knowledge base from these non-focus products. That the share of non-focus products on the line has a negative impact on current period productivity, but not on the firm's cumulative knowledge base is an important distinction for managers to keep in mind when considering the makeup of products on the production line. Managers should be wary of the costs to productivity of taking on too broad a portfolio of products. The firm is more likely to be able to leverage the established knowledge base when products are similar. Finally, similar to the organizational learning model, we again see in the knowledge transfer an increase in the parameter representing the transfer of knowledge from older to newer focus products suggesting that we may be underestimating this transfer in prior results.

Impact of Process Difficulty: We utilized details we collected through a survey on the relative difficulty of processes to capture differences in process difficulties across our focus products. It was important to control for process difficulty in our models to make sure that our organizational learning, knowledge transfer, and product mix coefficients were not accidentally capturing unobserved aspects of process difficulty. Given that our process difficulty measures were limited to the focus products we were unable to see the impact of process difficulty in the more limited learning model. We were, however, able to gain insights in the knowledge transfer model. Each difficulty measure (training time, engineering rank, and training process categorization) captures a unique element of process difficulty. We see that, in general, increased difficulty has a negative impact on productivity and that both our learning and knowledge transfer results are robust when controlling for difficulty.

Due to differences between initial training time and on-the-line task implementation, we find limited insights from our training time measure. We find that the greater the share of criteria-based processes on the line the lower firm productivity. Finally, our engineers' ranking of process difficulty seemed to capture process difficulties across process types effectively – the greater the average difficulty of the processes on the line, the lower the productivity.

Impact of Product Variation: With measures for the minor product variations requested by customers across unique part numbers we are able to have a more nuanced discussion of the impact of product variation on the production line. We find that our insights from the Herfindahl Index hold strong – that increased heterogeneity within the high-level focus product groupings is beneficial for productivity. At the same time, increased minor product variations within the focus products (to meet customer specifications) is harmful to productivity. Likewise, increased variation in non-focus product part numbers (which may be minor or major differences based on the base product) is also harmful to productivity. When we account for these part number variations we see that the learning rate in the firm no longer decreases over time. We also see increased transfer of knowledge forward from older to newer generations of focus products.

The detail on part numbers per volume for both focus and non-focus products also allows us a more careful look at the significance of the share of non-focus products on the line for current period productivity. When we account for the part number variation measures, we no longer see a negative impact on productivity from an increased share of non-focus product in the learning model – the negative impact of the high mix within non-focus products is captured in our part number variables. In the knowledge transfer model, we see a reduced negative impact of per-period share of non-focus products on current period productivity and we no longer see a detrimental impact of non-focus products on the firm's knowledge base. In both models, our part number variable provides a possible explanation for the challenges with non-focus products. Importantly, it does not, however, change the positive impact of having heterogeneity of multiple generations of the focus product on the line at once, as these results remain robust.

Overall, having added in measures for process difficulty and minor product variations, we continue to find strong support that our firm learns from its experience while producing a wide array of products. We see that the firm's learning rate may not, in fact, decrease over time and more knowledge may be transferring to new generations of focus products than originally estimated. While non-focus products bring challenges to the production line, the harmful effect of increased shares of non-focus products may not be as harsh as our earlier models indicated.

We see that product mix can have different impacts within our firm, depending on the extent of variation. We see that an increase in minor product differences to meet customer specifications reduces current period productivity. As with non-focus products, the firm may see benefits from revenue from these customer-specific products that may offset the productivity losses associated with them. However, an increase in heterogeneity of generations of the focus product on the line is beneficial for firm-productivity. Additionally, we see that the firm is able to transfer a significant amount of knowledge across generations of focus products.

Chapter 7

Conclusions

This work illuminates the roles of learning and knowledge transfer in a multi-product production setting. We focus on production dynamics within a single firm to allow us to focus on elements of the firm which drive knowledge creation.

We leverage ten years of data collected over three site-visits to our firm's offshore manufacturing facility to shed insights into organizational learning and cross-product knowledge transfer when a factory floor manages a varied product portfolio. We study how our firm learns from three levels of product mix and how it is able to transfer knowledge across certain product types. We hope these insights contribute to advancing the state of knowledge on knowledge acquisition and retention.

In this final chapter, we first provide an overview of our findings on the different levels of product mix and their impact on learning and knowledge transfer. We then discuss managerial implications. We end with a discussion on the generalizability, limitations, and policy implications of this work as well as future research directions.

7.1 Benefits of Bounded Diversity: Implications of Product Mix

The production and operations management literature generally starts from the assumption that producing a variety of products increases production costs. The literature then 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)]. In contrast, the organizational learning literature gives us cases where organizations learn more from diverse than homogenous experiences, where product heterogeneity is beneficial for learning, and where changes in product mix stimulate more efficient resource allocation [Haunschild and Sullivan (2002), Schilling et al. (2003), Bernard et al. (2010), Wiersma (2007)].

Our results reconcile some of these differences across the organizational learning and production and operations management literatures by determining when product mix heterogeneity is valuable and when it is harmful. We find both advantages and disadvantages to product mix on the production line depending on the extent of the differences between the products on the line.

Our firm has two major categorizations of products – focus products and non-focus products. Focus products are a family of similar products that evolve though product generations, and comprise the majority (86%) of production volume. Non-focus products are a collection of products outside of the firm's high-volume focus. Non-focus products are often based on the same underlying scientific principles as the focus products, but vary in their form factor (and corresponding physical size ranging from 0.1 to 9 times the size of focus products) and in their end-use. Beyond these high-level product groupings of focus and non-focus products, we also consider changes in the focus product family across five generations and minor product differences – such as altered product specifications or packaging differences for individual customers.

We find that product heterogeneity within our focus products – in other words having multiple generations of products on the production line simultaneously – is beneficial for both short-term productivity and long-term learning. Specifically, an increase in heterogeneity within focus products boosts productivity and increases the firm's learning rate. Past work has also found that heterogeneity across related products in mature processes was beneficial to firm productivity in the context of sorting different types of mail [Wiersma (2007)]. In this mail-sorting case, Wiersma (2007) finds that organizational units which have higher diversity have a higher learning rate, but suggests that other mechanisms may also account for the benefits of heterogeneity such as knowledge transfer across products, or that work units which see a larger variety may have "a deeper cognitive understanding of the context of tasks and, therefore, are better able to learn" [Wiersma (2007)]. In our case, we see knowledge transfer across these focus products, but also find that focus product heterogeneity is beneficial to firm productivity beyond the benefits of generational knowledge transfer.

As indicated above, we find the firm is able to effectively transfer knowledge forward to new generations of the focus product. This knowledge builds over generations and perpetuates across all generations. In contrast, a study on DRAM production found knowledge to only transfer across one generation [Irwin and Klenow (1994)]. Irwin and Klenow used price data in their analysis, which is affected by many factors beyond learning and knowledge transfer at a specific firm. In addition to using a different measure than ours, differences in the empirical contexts could also contribute to the different pattern of result. Understanding market differences across these products is helpful in clarifying why we might see transfer across more generations in our high tech hardware components than Irwin and Klenow (1994) found in semiconductors. DRAM is a technology where the newest product completely replaces older products and there is very little advantage for a consumer to purchase an old version of DRAM. In the case of the hardware components in this study, customers continue to have specific needs for older generations and these older generations remain in active production for a long time. Other work looking at knowledge transfer across co-produced models of aircraft found, similar to this study, spillovers of knowledge from production of one model to another using firm-level data [Benkard (2000)]. The co-production of these product generations in both the Benkard and our own study may increase opportunities for learning to persist and knowledge to transfer to new generations.

In contrast to the above results, where having multiple generations of a product on the line is beneficial to productivity, there are other cases where a heterogeneous product mix can be detrimental. When products on the line are too different from one another – such as the large differences between the focus products (with their multiple generations) as well as within the large variety of non-focus products – this variety takes a toll on the firm's productivity. Likewise, minor variations – such as customer-specific alterations within a single generation of focus products – also have a negative effect on the firm's productivity. To our knowledge, no other studies have specifically looked at this level of product variation utilizing part numbers to capture both minor and major product variations. One study discusses the role of engineering changes on shared learning [Adler (1990)], but does not specifically look at the impact of product mix on productivity and learning.

The strategies suggested by the production literature to counteract the negative impacts of product variety, such as commonality in product and process design [Fisher et al. (1999), Desai et al. (2001), Suarez et al. (1995)], are leveraged across the firm's generations of its focus product, but are limited when we look across the focus/non-focus product boundary. Non-focus products bring in the complications that are largely associated with the downside of producing a variety of products within the production literature (such as planning, task scheduling, material and inventory management, and quality control) [Fisher et al. (1999), Gaimon and Morton (2005)]. Our results suggest that the benefits of focus product heterogeneity are counteracted by the challenges of manufacturing non-focus products. Producing these small volumes of a variety of non-focus products has a significant and negative impact on the firm through both first and second order effects – productivity and knowledge transfer, respectively.

The other boundary on our classification of product diversity is that of very minor product differences that come about through customer-specific variations. Similar to our product differences that are too major (in for the form of the non-focus products), we see minor product variations decrease short-term productivity. When we account for the variety that comes with managing a large number of minor product variations we see that doing so changes the shape of learning curve. When we do not include these minor product variations in our analysis we see the firm's learning rate decrease over time (though the firm continues to learn throughout our analysis). In contrast, when we control for the negative impact of these minor product variations, we see that the firm's learning rate remains constant over time. One possible explanation for this finding may be that the changeover in tooling or process-specific software tweaks is taxing to the production line [Denomme field notes (2011)]. Another possible explanation for this finding may be that process specifications associated with these minor product differences may be taxing to individual line workers by switching elements of their task and disrupting workflow.

As discussed in the previous two paragraphs, both producing small volumes of all varieties of non-focus products and producing customer-specialized focus and non-focus products have significant and negative impacts on the firm's productivity. Despite these negative impacts on productivity, we find that our firm is able to leverage having multiple generations of its high volume focus product on the line to increase productivity, in other words to learn. One mechanism helping explain this increase in productivity with more generations of product on the line, is the transfer of knowledge that we observe from older generations of products to the newer one.

To summarize the insights from our results, we see 1) the benefits of heterogeneity when we consider the focus product set versus the non-focus product set, 2) that heterogeneity within some boundary of product commonality (generations of focus products) increases learning and boosts productivity, and 3) too many minor and transient specifications decreases productivity . Each of these elements of product variety uniquely contribute to the production experiences from which the firm learns.

7.2 Managerial Implications

Our results show that the firm is seeing benefits of product diversity from the co-production of multiple product generations on the production line. We found that knowledge transfers forward across product generations; our firm is able to leverage its production experience to increase productivity on newer product generations despite any process differences in the products. These results suggest the firm is capable of learning from its experiences. Based on existing theories on organizational learning, we might expect that the firm is embedding knowledge from past production in one or several elements of its organizational context such as its tools (e.g. machinery, tooling), its tasks (e.g. routines, processes), or its employees [Argote and Miron-Spektor (2011)]. Our firm should be reassured that the mixture of different generations of their focus products is actually beneficial to their productivity.

We find that the benefits of product diversity are bounded on two fronts: 1) products that are too different in form factor or physical size and 2) minor product differences such as customer-specific product variations. Managers should be wary of the costs to productivity of taking on too broad a portfolio of products, when their products are too different in their form factor and purpose. Additionally, managers need to weigh the tradeoffs of the additional revenues they may receive by meeting individual customers' requests through tailored products, against the decrease in productivity associated with having more minor product variations on the line.

7.3 Discussion

7.3.1 Generalizations

Our findings have important implications for manufacturing facilities that manage a multitude of products in one location and see product variety at multiple levels. Our results suggest that industries that see products evolve through generations may benefit – in terms of productivity – from having co-production of older products at the same time as newer ones in the same facility.

We expect our results may be most likely to be replicable in other factories with largely labor-driven production processes. The manufacturing processes in our firm are largely not automated; tooling aids the line workers in assembly steps and testing protocols are built into testing machinery, but the production line is heavily dependent on direct labor. While we have not been able to pinpoint the underlying mechanism explaining why having multiple generations of products on the line increases productivity and contributes to the firm's rate of organizational learning, we do know that knowledge transfers from the older to the newer products. In a low-capital context such as our firm, this learning from experience and transfer of knowledge are most likely embedded in training procedures, equipment on the line, line and station set-up, and the workers at various levels within the firm. Indeed, in the case of our firm, new line workers go through a carefully designed training and certification period, much of the tooling and machinery was developed by the firm, and engineers and managers spend a lot of time in meetings discussing production improvements and on the production line actively communicating on areas for improvement [Denomme Field Notes (2008, 2011)]. Finally, several managers, engineers and trainers I spoke with during my site visits had been with the firm at this facility since the facility's inception and were a deep source of knowledge of the inner workings of the firm. These mechanisms for embedding organizational learning within the firm would be a particularly interesting area for future study. We do not know if similar results would hold in a more automated production facility. Learning in a completely automated manufacturing facility may be more concentrated in areas of product and process design such as in the tooling or machinery or in the design of the product for manufacturability.

7.3.2 Policy Implications

With 87% of U.S. output coming from multi-product production environments and over half of all U.S. firms altering their product mix every five years [Bernard et al. (2010)], understanding the performance dynamics of multi-product firms is important as the U.S. looks to future growth, particularly in the manufacturing sector of the economy.

Indeed, there has been significant recent federal interest in revitalizing U.S. manufacturing by developing leadership in "mass-customization" – low-volume, high-quality, fast-turnaround production of many products in a single facility or even on a single machine. To this end, several federal agencies are investing in advanced manufacturing processes, including DARPA's adaptive make program, DOE's Innovative Manufacturing Processes program focusing on additive manufacturing, and the National Additive Manufacturing Innovation Institute (NAMII) [NSTC (2012), DARPA (2011), DOE (2012), NAMII (2012)]. New manufacturing technologies, such as additive manufacturing, may alter the flexibility of certain process steps and subsequently change the ability to deal with a high mix, low volume product portfolio. In pushing forward with these initiatives, it will be important to better understand how much of the challenges associated with high product mix, such as tooling transitions [Womack et al. (1990)], can be overcome through the machines, and how much of the challenges of high product mix – such as those associated with differences in development [MacDuffie et al. (1996)] and scheduling [Fisher et al. (1999)] – still remain. Likewise, it will be important to understand how much of the productivity and learning benefits of high product mix, such as found in our study around having multiple generations of products on the line, can be captured in the more automated adaptive make and additive manufacturing software and machinery. For example, DARPA's adaptive vehicle make program vision aims to incorporate "instant foundries" with the capability for rapid switch-over between designs with a minimal learning curve and "mass customization" across product variants and families [DARPA (2011)].

Additionally, instead of or in parallel to these investments in new machines, opportunities may exist to to improve the productivity of existing facilities through more careful selection of product mix. Future research is needed to determine whether these new manufacturing processes achieve their aims and whether our findings would replicate in contexts using them.

7.3.3 Limitations and Future Work

The most limiting element of the data we collected is the inability to distinguish labor input by product type. This limited our analysis by constraining us to always consider the entire production output. Additional data, such as hours per product grouping, would allow us deeper insights. Being able to distinguish labor by product grouping over time would enable us to see how productivity changes over time for each product grouping and how productivity in each product grouping is impacted by product variety within that grouping. We could also develop a more fine-grained analysis on knowledge transfer.

A second limitation facing our study is that our process difficulty variables are limited to only focus products. Process listings of the 14 major product groupings with the non-focus products along with followup surveys on process difficulty with trainers and engineers would allow us to extend our analysis on the role of process difficulty and process commonality on learning and knowledge transfer to the non-focus products.

In this study we were unable to determine exactly what mechanism is underlying the increase in productivity associated with heterogeneity across generations of the focus product. We see that knowledge transfers forward to new generations. We also see that variation across generations of the focus product is helpful for firm productivity when multiple generations are simultaneously produced in the same facility. Thus, there appears to be a benefit to cross-generational focus product heterogeneity over and above the effect for knowledge transfer. Future work could seek to better understand the mechanism(s) underlying this productivity benefit by investigating how much knowledge is embedded in each of primary tenets of organizational context (i.e. tools, tasks, and members) and if knowledge transfers more or less easily through one of these particular elements. In this case, data on employee movement both within and across firm boundaries could shed insights into employees as a repository of knowledge, data on training procedures and how they have evolved over time could shed insight into how much production knowledge is embedded in the training process and how much of that knowledge is transferred to line workers, and a study of the evolution of the machinery required for each process could shed insight into how much knowledge is embedded into the primary physical tools of the firm.

Another future research avenue to consider is the implications of offshoring and outsourcing when there are potential benefits to co-production in a multi-product environment. Future work could investigate if firms that are outsourcing production to an outside facility or firm are giving up an opportunity to learn, and if a parent firm's skills atrophy when production is outsourced. Yet other work in this vein could investigate if contract manufacturers are uniquely situated to learn from the production of product generations and if they are able to transfer knowledge across broader product types across their customers.

A final limitation is that our study is limited to one firm. While studying only one firm allows us to focus on a specific multi-product context, gain a deep understanding of the organization, and collect a rich dataset, it will be important to test the implications of the extent of product heterogeneity and variation on learning and knowledge transfer in additional settings. The increase in automation in mechanical assembly factories makes the automated production setup compelling as a closely related context for future study. Alternately, the production setup of completely different industries, such as pharmaceuticals or chemicals where production processes are quite different than those in mechanical assembly, could shed further light into the roles of processes as a mechanism of knowledge transfer. It would be particularly interesting to see the methods and models developed in this study applied in these other contexts to further develop our understanding of the mechanisms behind learning and knowledge transfer in multi-product production environments.

Appendix A

Sample Surveys

Interview Sheet: Process Commonality & Difficulty

This is a written survey sheet provided by researchers at Carnegie Mellon University. This study is looking at organizational learning and knowledge transfer across products at [focus firm]. Your responses here will be kept confidential by the study investigators. If you have any questions please contact Carolyn Denomme by email at cdenomme@cmu.edu or by phone at [].

Background Information:

What is your name?

What is your position title at [focus firm]?

What is your email address and phone extension (will only be used for questions on survey)?

When did you start working at [focus firm]?

What production area do you work in (example: [stage 1, stage 2], etc.)

What types of products or processes have you worked on during your tenure at [focus firm]?

Questions on Processes & Products:

For questions that ask about specific product families, please only fill out information on products that you have worked with directly.

1. In your mind, what makes products similar during production (for example, [end use application], [attribute (A or B)], products that undergo certain process steps, products that have a specific form factor or component)?

2. Please describe your experience with implementing a new product on the production line. Please be as specific as possible.

3. Please rate each process step for each grouping of products based on difficulty for the line worker on a scale of 1-5 where 1 is very simple, 2 is simple, 3 is neutral, 4 is difficult, and 5 is very difficult.

Table 3.1: Process Difficulty by Product Type for Testing Processes

Process Step	1a	1b	2a	2b	3a	3b	4a	4b
Process Step 1								
Process Step 2								
…								
Process Step 77								

4. For your production area, what percentage of machines are used on both products in a given box below?
   Example for bold box: x% of machinery used for 1a products is also used for 1b products.

	1a	1b	2a	2b	3a	3b	4a	4b
1a								
1b								
2a								
2b								
3a								
3b								
4a								
4b								

5. For your production area, what percentage of trainers have ever worked on both products in a given box below?
   Example for bold box: x% of trainers who work on 1a products have also ever worked on 1b products.

	1a	1b	2a	2b	3a	3b	4a	4b
1a								
1b								
2a								
2b								
3a								
3b								
4a								
4b								

6. For your production area, what percentage of technicians have ever worked on both products in a given box below?
   Example for bold box: x% of technicians who work on 1a products have also ever worked on 1b products.

	1a	1b	2a	2b	3a	3b	4a	4b
1a								
1b								
2a								
2b								
3a								
3b								
4a								
4b								

7. What percentage of engineers have ever worked on both products in a given box below?
   Example for bold box: x% of engineers who work on 1a products have also ever worked on 1b products.

	1a	1b	2a	2b	3a	3b	4a	4b
1a								
1b								
2a								
2b								
3a								
3b								
4a								
4b								

8. For your production area, please list any major tool or equipment changes (if any) that have happened. (For example: new oven, more production lines, new soldering equipment, new automated machinery, etc.)

Year	**Major tool or equipment changes**
2001	
2002	
2003	
2004	
2005	
2006	
2007	
2008	
2009	
2010	
2011	

Interview Sheet: Process Commonality & Difficulty for Trainers

This is a written survey sheet provided by researchers at Carnegie Mellon University. This study is looking at organizational learning and knowledge transfer across products at [focus firrm]. Your responses here will be kept confidential by the study investigators. If you have any questions please contact Carolyn Denomme by email at cdenomme@cmu.edu or by phone at [].

Background Information:

What is your name?

What is your position title at [focus firm]?

What is your email address and phone extension (will only be used for questions on survey)?

When did you start working at [focus firm]?

What types of products or processes have you worked on during your tenure at [focus firm]?

1. Please describe each type of process (simple, skill-based, criteria-based, special case, hazardous, other) and list how long it takes on average to train a manufacturing specialist in that process.

Table 1: Process Categorization of Processes

Process Step	Type of Process	Training Time
Process Step 1		
Process Step 2		
....		
Process Step 77		

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