Experience-based learning in innovation and production

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How can we model and document the impact of experience in product innovation? We use data on the innovation and production histories of 294 product platforms to explore experience-based learning. We extend learning curve concepts from their traditional domain – the production process – into the product innovation process to build and test a richer, quantitative model of learning. The results suggest that learning occurs differently in the innovation process than in production. They also suggest that how and where a firm learns depend in part on the complexity of product components and sub-systems. Finally, we discuss the competitive implications for product innovation.

1. Introduction

If a company wants the most benefit from experience-based learning, should it make a relatively small number of products in high volume and over a long time, or should it keep introducing new products with shorter life-spans and lower production volumes? This study extends innovation literature by adapting one of the cornerstones of production research – the learning curve (e.g. Adler and Clark, 1991) – to create a model in which a firm innovates and then produces new products, thus applying and strengthening capabilities in innovation and in production. By applying traditional learning curve concepts to the product innovation process, we move learning curve methodology beyond the narrow traditional production domain. We use a unique data set on the innovation and production of almost 300 product platforms in the American car market.

The paper makes several contributions. It offers an experience-based learning model that distinguishes between the innovation and production processes. Second, it suggests that the locus of learning may vary depending on the complexity of the components in products. Third, by testing the model in the context of product quality, the paper moves beyond the efficiency focus that has dominated the majority of empirical studies of experience-based learning.

Learning through experience in production has been documented extensively, but what about in the innovation process? Whether by innovation or imitation, all firms engage in a product innovation process (Walsh et al., 1992, p. 16). For the purposes of this paper, we assign "innovation process" a rather specific meaning. It is the set of activities collectively known as the product design stage, or the product development stage – the set of activities which occur before regular production begins. The purpose of this process is to create new product designs, or platforms. These platforms may be used for one version only, or for multiple variants. Airbus, for example, used its first aircraft design – the A300 platform – for more than 30 years. Changes were evolutionary, and over time the firm introduced numerous variations on the basic design. As another example, Chrysler used one basic automotive platform design – the K-car – to produce a variety of models over a 15-year period.

The results pose some important implications for managers and for researchers. A firm's decisions about product innovation and the production process will influence where, how, and how much it can learn. For example, a firm's strategy may be to differentiate itself on the basis of frequent introduction of new platforms in order to satisfy/stimulate market desires for novelty and thus gain a competitive advantage. That choice will lead to greater innovation experience and, we argue, a better innovation process. Conversely, a firm with an innovation strategy focused on improving or leveraging existing platforms gains, *ceteris paribus*, more experience in the production process.

Further, if a firm reaps substantial benefits from learning in its production process, we should also consider that these positive effects may be due in part to limited experience in product innovation and development. In other words, experience in the production process does not equate to experience in the product innovation/design process.

Additionally, a product's relative complexity may affect where a firm can or should look for improvement. Improvements in relatively simple products may come from production runs over a long period of time, while complex products may benefit more from producing at a rapid rate. Production rate and length of time appear to influence learning independent of cumulative experience.

Finally, the study highlights the importance of managing and studying a company's activities as a set of inter-related processes. Those processes can be quantified, they may manifest measurable learning effects, and they may influence learning in different ways.

2. Background

2.1. Learning curves

The learning curve rests on the simple concept of experience-based learning – in other words, practice makes perfect. Wright (1936) noticed that learning in aircraft production followed a pattern – as subsequent units were manufactured, the time needed per unit dropped at a fairly uniform rate. This focus on cost reduction as the evidence of learning found its way into mainstream management research (e.g. Andress, 1954). Indeed, with few exceptions the learning curve literature still focuses on learning as productivity improvement.

2.2. Experience-based learning: competitive issues

A strategic, competitive view of the topic is significant for understanding product innovation in the context of competition. In addition to some earlier work on the various effects of learning on market structure (e.g. Spence, 1981; Hall, 1984; Hall and Howell, 1985; Amit, 1986; Majd and Pindyck, 1989; Cabral and Riordan, 1994), some studies have begun to disaggregate the components of learning (e.g. Adler and Clark, 1991; Zangwill and Kantor, 1998).

Experience-based learning has dramatic implications for competition and market structure. For example, learning can foster a self-reinforcing market dominance driven by the leading firm's continuing cost advantage (Cabral and Riordan, 1994). As cost declines, so does the market price at which the firm finds it uneconomical to produce (Majd and Pindyck, 1989). However, that advantage may not remain constant and learning and cost may not be perfectly correlated (Devinney, 1987). Gulledge and Womer (1990) suggest that, in terms of cost, there may be a trade-off between learning and production rate – in order to minimize total cost, the production rate should change over the production life of a good. A firm's learning is likely to deter new competitors and lead to industry concentration (Spence, 1981; Hall, 1984), and competing in markets with short product cycles and long learning periods is especially difficult (Mody and Wheeler, 1987). Even though the diffusion of learning between firms (e.g. Ghemawat and Spence, 1985) may facilitate entry, an incumbent with a substantial lead in experience may reduce an entrant's chances of survival (Lieberman, 1987, 1989; Chu, 1988). For example, Terwiesch et al. (2001) discuss the competitive benefits of reducing 'time to volume' (rapid accumulation of production volume), and the attendant experience-based improvements in cost and quality.

Certainly, experience-based learning is a key issue for many firms. For example, firms facing price-elastic demand, if they are to grow in profitability or sales volume, must learn to produce more efficiently. Firms facing direct price competition have a strong incentive to learn how to increase efficiency or differentiation faster than their competitors. Similar competitive pressures affect firms in markets with substitute products and firms in shrinking markets.

Table 1. Summary of selected learning curve research

Author and Date	Focus of learning curve
Linton and Walsh (2004)	Cost-reduction
Jaber and Bonney (2003)	Quality and productivity
Terwiesch et al. (2001)	Production yield (and others)
Chung (2001)	Production yield
Zangwill and Kantor (1998)	Cost-reduction (with mention of others)
Cabral and Riordan (1994)	Cost-reduction
Dorroh et al. (1994)	Cost-reduction
Frischtak (1994)	Cost-reduction
Gruber (1994)	Production yield
Adler and Clark (1991)	Productivity
Briscoe and Roark (1991)	Cycle-time reduction
Cook (1991)	Cost-reduction
Fields (1991)	Cost-reduction
Kantor and Zangwill (1991)	Cost-reduction
Adler (1990)	Productivity
Gulledge and Womer (1990)	Cost-reduction
Bailey (1989)	Cycle-time reduction
Golightly (1989)	Quality improvement
Lieberman (1989)	Cost-reduction
Majd and Pindyck (1989)	Cost-reduction
Meredith and Camm (1989)	Cost-reduction
Chu (1988)	Productivity
Boucher (1987)	Productivity
Devinney (1987)	Cost-reduction
Lieberman (1987)	Cost-reduction
Lowenthal (1987)	Productivity
Mody and Wheeler (1987)	Cost-reduction
Amit (1986)	Cost-reduction
Dorroh et al. (1986)	Cost-reduction
Fine (1986)	Quality and cost-reduction
Hiller and Shapiro (1986)	Cost-reduction
Ross (1986)	Cost-reduction
Smunt (1986)	Productivity
Camm (1985)	Cost-reduction
Ghemawat and Spence (1985)	Cost-reduction
Hall and Howell (1985)	Cost-reduction
Tanner (1985)	Cost-reduction
Vickson (1985)	Cost-reduction
Hall (1984)	Cost-reduction
Jewell (1984)	System failure reduction
Lieberman (1984)	Cost-reduction
Spence (1981)	Cost-reduction

2.3. Limitations of prior research

This study addresses significant limitations of prior learning curve research – the neglect of the product innovation process, the focus on cost as the outcome of learning, and the lack of attention to the impact of product complexity.

Learning curve research from Wright (1936) forward shows that production experience can dramatically affect marginal cost. In addition to a focus on the *production* process, extant research is preoccupied with *productivity* (or cost reduction) as the significant capability built through experience-based learning. Most studies focus on learning primarily in terms of cost reduction or productivity improvement (typically expressed as labor time or cycle time) as a function of accumulated production. That is, they look at changes either in the numerator or the dominator of the productivity ratio – changes in output volume with constant input, or changes in input cost or quantity with constant output. Although there are many possible measures of learning other than cost reduction (Yelle, 1979; Zangwill and Kantor, 1998), exceptions are rare in empirical research. They include quality (Fine, 1986; Jaber and Bonney, 2003) defective output (Gruber, 1994), and capacity planning (Smunt, 1986) (Table 1).

The typical focus on productivity as the dependent variable has at least four major weaknesses. First, scale economies may be mistaken for learning (Amit, 1986; Dorroh et al., 1986). Second, researchers rarely control for changes in input prices, even though such changes directly affect the dependent variable being studied.

Third, reducing the marginal cost of production is only one element of a firm's competitive strategy. For example, in markets with proliferating products, cost advantages from scale or experience-based learning are hard to achieve, and a narrow focus on cost obscures the competitive significance of such things as innovation, service and, especially, quality.

Fourth, studies of experience-based learning have not addressed the issue of component or sub-system complexity. Many products are combinations of complex and simple components. A complex component or sub-system may itself have numerous components and may be characterized by relatively stringent manufacturing, assembly, and operating tolerances. On the other hand, relatively simple components or sub-systems represent a lower degree of functional complexity and a lower degree of component aggregation.

They also are likely to have less stringent manufacturing, assembly, and operating tolerances. For example, consider the complexity and physical precision of the insides of a computer hard-disk or CD-drive as compared with the metal frame to which both are attached inside a computer case.

However, such differences in product complexity represent a critical issue in product innovation and production. We will argue that such differences influence where and how a firm learns through experience. Furthermore, a firm's component decisions directly raise the subject of *how* companies enhance learning (Mikkola, 2003, p. 440).

3. Model and hypotheses

The result of the product innovation process may be a variation on an existing product, or it may be a new product design or platform. We follow the definition of Walsh et al. (1992, p. 16), in which a product platform is 'the configuration of materials, elements and components that give a product its particular attributes of performance, appearance...[and] method of manufacture.' From this perspective, not only do new platforms look and behave distinctively, they require distinctive production processes, significant alteration of existing ones, or re-configuration of flexible manufacturing systems. At the platform level of analysis, similar products share basic commonalities of product characteristics, performance, and production system. A firm may develop thematic variations on a central platform (Blaich and Blaich, 1993), such as enhanced, customized, cost-reduced, and hybrid variations (Wheelwright and Sasser, 1989). Nonetheless, variations retain a degree of common core technological and production characteristics (Walsh et al., 1992).

Products are the embodiment of learning. They manifest a firm's knowledge about innovation and production. The model in this paper suggests that the learning manifested in a product platform is a function of several factors:

> *Learning = F(a platform's cumulative production volume, age of the platform, production rate, the firm's internal experience in developing new platforms, and the diffusion of industry experience in developing new platforms)*

Figure 1 illustrates our model. The learning embodied in a product platform is a consequence

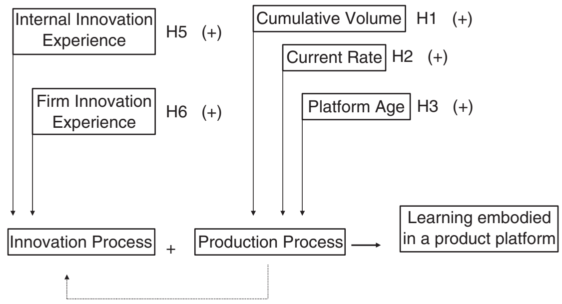

Figure 1. Determinants of the learning embodied in a product platform.

of learning in the (1) product innovation process and (2) the production process.

In brief, these two fundamental processes contribute to learning in the following way: First, the factors in the production process that support learning are the firm's experience in producing a given platform, the platform's rate of production, and the total time the firm has chosen to use the platform. Second, learning in the innovation process comes from the firm's own prior experience in that process and from the industry's aggregate prior product innovation experience. As in the production process, these factors represent learning driven by accumulations within processes.

3.1. Platform volume

At the platform level, the volume-learning relationship logic echoes the traditional product-level argument – the accumulation of volume leads to learning through experience. Furthermore, using a given platform for a greater portion of total production volume may positively affect experience-based learning through higher production volume of individual components (Fine, 1986) and through the benefits of standardized production systems (Collier, 1981; Ishikawa, 1982, 1985; Feigenbaum, 1983; Deming, 1986). Thus,

Hypothesis 1. *Platform volume is positively associated with learning.*

3.2. Platform production rate

Just as a firm may learn from past experience, it may learn from present experience. One may also apply learning curve theory to explain the influence of the current rate of production on learning. The platform production rate is the rate of production using a particular platform in a given period and is independent of previously accumulated production volume. Within a given period, the higher the production rate the more experience the firm gains. Because learning may occur continuously, a model of learning based on previous experience may be strengthened by incorporating the impact of current activities. Thus,

Hypothesis 2. *Platform production rate is positively associated with learning.*

3.3. Platform age

Resource-based theory (e.g. Wernerfelt, 1984; Barney, 1986; Dierickx and Cool, 1989), in which a firm's resources may be strengthened by the impact of time, sheds light on the relationship between learning and the time passed since the introduction of a platform. Since time provides opportunity for reflection, experimentation, analysis, and synthesis, learning should not depend solely on production volume or rate.

Long production runs are desirable for learning (Smunt and Morton, 1985; Towill, 1985; Bailey, 1989). For example, Boeing's 747 aircraft has been in production for almost four decades. Jet aircraft production volume is relatively low compared with many products – Boeing's total cumulative production is measured in the thousands, while General Motors' is in the hundreds of millions. However, the length of 747 production has given the firm time to develop iterations on one basic platform, incorporating refinements and changes which took time to conceive, develop, and implement. This opportunity for refinement is a function of time, not volume. Thus,

Hypothesis 3. *Platform age is positively associated with learning.*

3.4. Innovation experience

Product innovation, like production, is a process in which learning can occur, driven by similar factors. However, any model of learning in the innovation process also should incorporate a major source of learning for a firm – the experience of other firms.

Innovation experience denotes the accumulated experience in the process of innovating and implementing product platforms. The logic of the experience-learning relationship simply shifts the learning curve concept to the innovation process. That is, repetition – the accumulation of innovation experience – should enable learning.

Our model reflects a firm's two sources of applicable experience – its own internal innovation experience and the innovation experience of other firms. Just as an improved production capability should lead to better products, so too should an improved innovation capability:

> ' ... *[It] is believed to have a direct impact on ... [products] through its effect on product reliability, product features, and serviceability ... [and] an indirect effect ... through the impact of design* ... '(Flynn et al., 1994)

3.4.1. Internal innovation experience

A firm's capabilities should grow as it accumulates 'production' of new platforms, production process designs, and ramp-ups to regular production. However, learning curve literature has paid modest attention to the effect on productivity of pre-production learning (Briscoe and Roark, 1991) and up-front effort (Golightly, 1989). In addition to knowledge gained in direct production – 'intra-task learning' – knowledge also grows in the planning stages – 'pre-production learning' (Briscoe and Roark, 1991). The innovation process, the design of production processes (industrial engineering), and production ramp-up clearly would fall into Briscoe and Roark's pre-production learning stages, while Adler and Clark's (1991) 'managerial' variables – engineering changes and workforce training – could happen either before or during production. Repeating these activities over time should help incorporate learning from previous platforms into new ones. Repeating this product development process should increase the learning embodied in new platforms (Stalk and Hout, 1990; Wheelwright and Clark, 1992).

Focusing on the innovation process may also enable learning by enhancing interaction and cooperation. It may change a firm's relationships with its suppliers from a pattern of 'exploitative contractual relations' centered on bargaining, to a symbiotic pattern of 'problem-solving' (Poirier and Houser, 1993; Nishiguchi, 1994). For example, research has documented the tight supply links in the Japanese auto industry (Cusumano and Takeishi, 1991), an industry that has demonstrated tremendous growth in knowledge, in contrast to the more arms-length links in the historically troubled British auto industry (Turnbull et al., 1992). Thus, Hypothesis 4. *The firm's internal innovation experience is positively associated with learning.*

3.4.2. Industry innovation experience
Innovation diffusion literature shows that competition encourages imitation of innovations; as Ghemawat and Spence (1985) point out, diffusion of learning should affect firms' relative performance. Clearly, a competitive environment is particularly likely to encourage firms to seek and apply the experience of others (e.g. Appleyard, 1996). Although economic incentives and practical mechanisms (e.g. patent protection, non-compete clauses in employment contracts, employee retention efforts, and secure facilities) may slow the diffusion of knowledge, various mechanisms facilitate it. Perhaps the most obvious of these is reverse-engineering; other mechanisms are professional associations, trade publications, and relationships between firms and their suppliers, competitors, and distributors for production, marketing, and research. Thus,

Hypothesis 5. *The industry's cumulative innovation experience is positively associated with learning.*

4. Empirical study

4.1. Data and sources

The empirical test of the model uses archival data on all makes and models of passenger automobiles sold in the United States [excluding trucks, vans, sport-utility vehicles (SUVs), and cars with extremely low sales volumes]. The industry often uses production lines to make a variety of models based on one platform, so we aggregate and weight data on individual car models to derive platform-level data. Flammang (1988, 1994), Gunnell (1992), and *Ward's Automotive Yearbook* provide the industry criteria for aggregating to platforms.

The proxy for experience-based learning is product quality, measured as reliability. The dependent data come from the detailed 'frequency-of-repair' survey statistics contained in *Consumer Reports* (*CR*) magazine. The study period is two and a half decades – 1965–1988. This is an attractive study period for several reasons. First, *CR*'s methods of analysis and reporting remained essentially unchanged. The magazine's statistical methods began to change beginning in 1989; any analysis that spanned the change would be difficult to interpret. Second, the late 1980s to early 1990s saw the rise of the SUV market – including this new and highly distinct market segment likely would have clouded the analyses. In contrast, the market segment classifications used as controls in our analyses were quite distinct and constant during the period of our study. Third, our period of analysis captures the dramatic US sales growth of European and Japanese, cars, allowing us to recognize and verify differences based on region of origin, and to control for those differences in order to provide a more accurate and meaningful test of the model.

Since reliability is a long-run issue, the study uses data from the third calendar year after the model year of a vehicle. We chose to use five *CR* categories. For complex sub-systems, we used *CR* data on automatic transmissions and engines, by far the two most functionally complex sub-systems of automobiles – many components, extremely stringent tolerances, and aggregation before final assembly of the vehicle. For simple sub-systems, we used *CR* data on auto bodies, suspensions, and manual transmissions. These have complex manufacturing processes but are functionally simpler – fewer parts, relatively looser tolerances than the complex sub-systems, and less pre-assembly aggregation.

We derived data from Flammang (1988, 1994), Gunnell (1992), and *Ward's* for the independent variables (platform volume, age, variety, and experience) and the control variables (model year, region of origin, and market segment).

To generate data at the platform level of analysis, 2,500 records of data on individual car models are aggregated by weighting for relative sales volumes of models sharing a common platform. This yields a final dataset of 1,411 records representing innovation and production histories over 24 years for 293 product platforms.

4.2. Variables

The independent variables include *VOLUME* (natural log of platform volume), *PRODRATE* (natural log of platform rate), *AGE* (natural log of platform age), *INTERNALEXP* (a firm's internal innovation experience), *INDUSTRYEXP* (industry innovation experience), and three sets of dummy variables for the control variables of *REGION* (region of origin), *SEGMENT* (market segment), and *MODELYEAR* (model year). The two dependent variables derived from a factor analysis of the CR data are *COMPLEXQUAL* and *SIMPLEQUAL*, for complex

Table 2. Factor analysis: factor scores

	Factor 1	Factor 2
Engine	0.146	0.768
Automatic transmission	0.062	0.828
Suspension	0.773	−0.083
Manual transmission	0.690	0.204
Body	0.690	0.088
Eigen values		
Before rotation	1.78	1.13
After rotation	1.57	1.33
Variance explained		
Before rotation	35.5%	22.6%
After rotation	31.4%	26.6%
Total variance explained		58.1%

and simple sub-systems. When necessary, variables are weighted to reflect unequal production volume between models based on a common platform.

Let $f = 1..N_f$, denoting a Firm f.
Let $d = 1..N_d$, denoting a Platform d.
Let $m = 1..N_m$, denoting a Model m based on Platform d.
Let $n = 1..50$, denoting the 50 United States.
Let $y = 1..N_y$, denoting the years 1965 to N

The general mathematical model is

$$\begin{aligned} &COMPLEXQUAL_{f,d,y} SIMPLEQUAL_{f,d,y} \\ &= \alpha + \beta_1 VOLUME_{f,d,y} + \beta_2 PRODRATE_{f,d,y} \\ &+ \beta_3 AGE_{f,d,y} + \beta_4 INTERNALEXP_{f,d} \\ &+ \beta_5 INDUSTRYEXP_d + \beta_6 REGION_{f,d,y} \\ &+ \beta_7 SEGMENT_{f,d,y} + \beta_9 MODELYEAR_{f,d} + \varepsilon. \end{aligned}$$

4.3. Dependent variables

CR developed its scores based on analyses of several hundred thousand vehicles per year. We converted and coded *CR*'s scores for the chosen five categories (2,500 car-model records, or some 12,500 datapoints) and aggregated this car-model-level data into weighted platform-level scores.

Principle components factor analysis (using quartimax rotation to maximize the single-factor loading of each variable) produced high loadings for the dependent data and yielded two factors with eigen values over 1 (Kaiser, 1960), as shown in Table 2. Together, they account for 58% of the variance in the data.

The complex sub-system variables (engine and automatic transmission) load very heavily on one factor and the three simple sub-system variables load on the second. Our subsequent modeling uses two dependent variables: $COMPLEXQUAL_{f,d,y}$ and $SIMPLEQUAL_{f,d,y}$, the natural logs of the two factor score-derived variables.

4.4. Independent variables

$VOLUME_{f,d,y}$, is the natural log of the accumulated production (in units of 100,000) of the platform d in firm f as of the beginning of Model Year y. For statistical purposes, the accumulated production for the first year is defined as 0.005, rather than 0.

$PRODRATE_{f,d,y}$, is the natural log of the annual rate of production (in units of 100,000) of the platform d in firm f in Model Year y.

$AGE_{f,d,y}$, is the natural log of the age of the platform d in firm f in Model Year y. For statistical purposes, the first year of use is defined as 1, rather than 0.

These three variable use natural logarithms to fit regression's normality assumption and the traditional learning literature expectation of a non-linear relationship with the dependent variable.

$INTERNALEXP_{f,d}$ is a firm's accumulation of experience in the process of introducing successive platforms. It is a chronological serial platform number based on the history of platform introductions within a firm.

Similarly, $INDUSTRYEXP_d$, the industry's cumulative innovation experience that may be embodied in a given platform, is a chronological serial platform number based on the history of platform introductions across firms. For years in which the industry introduces more than one

Table 3. Descriptive statistics

	Mean	Standard deviation	Minimum	Maximum
Platform's cumulative unit production	400,000	800,000	2,000	5,978,000
Platform's age in years	4.8	3.4	1	17
Platform's annual production rate	132,000	200,000	2,000	1,314,000
# of platforms used by firm for each 100,000 units	6	4	1	[1]
Change in # of platforms used by firm for each 100,000 units	0.07	0.5	−2.7	1.2
Firm's innovation experience before this platform	13.2	11.7	1	50
Industry's innovation experience before this platform	127	66	1	293

[1]Not meaningful due to some firms' low total volume. $N = 1{,}411$ observations of 271 different platforms.

Table 4. Binary correlation coefficients

Variable	Mean	SD	1	2	3	4	5
1. *VOLUME* (LN)	0.655	2.652	1.00				
2. *AGE* (LN)	1.312	0.743	−0.556**	1.00			
3. *RATE* (LN)	0.764	1.611	−0.359**	−0.220**	1.00		
4. *SIMPLEQUAL* (LN)	0.708	0.961	−0.088	0.274**	0.020	1.00	
5. *COMPLEXQUAL* (LN)	1.242	1.634	−0.019	0.002	0.248**	0.040	1.00

$^{**}P < 0.01$.

platform, the higher number is assigned to the platform from the corporation with more internal innovation experience.

4.5. Control variables

$REGION_{f,d,y}$, a platform's region of origin, allows us to control for widely recognized and significant (e.g. Womack et al., 1990) differences between European, American, and Japanese carmakers in manufacturing and development practices – differences that were particularly salient over the period at hand (1960s–1990s). It also controls for the substantial non-US sales by Asian and European makers that are not otherwise captured in the data. As expected, the results of a MANOVA demonstrated a highly significant relationship between region of origin and the dependent variables, so we used a dummy-coded *REGION* as a control in the subsequent analyses.

The dummy variable $SEGMENT_{f,d,y}$ controls for market segment differences which are expected to explain some variation in quality. For example, luxury goods in many markets often use better materials and technological advances. We use the nine-segment industry standard taxonomy published in *Ward's*. As expected, the results of a MANOVA demonstrated a highly significant relationship between quality and market segment, so we retained *SEGMENT* as a control in the subsequent analyses.

The dummy variable $MODELYEAR_{f,d}$ is used to indicate the model year for each annual record of firm f's platform d.

5. Analysis and discussion

See Table 3 for summary statistics of the data.

As the table indicates, the typical record represents a platform which has been used already for 400,000 units, is almost 5 years old, and is produced at a rate of 132,000 units a year. As expected, cumulative volume, age, and rate vary substantially across the data set. The 'average' platform is used by a firm employing six different platforms for every 100,000 units; this reflects the number of smaller firms (mostly imports) in the market and the number of lower-volume platforms from many of the large firms. The average platform also is the 13th platform the firm has introduced.

Table 4 below reports means and binary correlations for the data:

Tables 5 and 6 summarize the results of regressing simple and complex sub-system data on the production and innovation variables.

Tables 5 and 6 suggest that the control variables were appropriately chosen and that they have significant explanatory power. They explain 22.1% (Total R^2) of the variance in simple sub-systems, and 18.7% in complex ones. The results for *MODELYEAR* suggest that when the

Table 5. Regression results – platform and innovation variables impact on learning in simple sub-systems

	Model 1a	Model 1b	Model 1c	Model 1d	Standardized β coefficients
Controls					
MODELYEAR (23 dummy variables)	Significant***				
REGION (two dummy variables)		Significant***			
SEGMENT (eight dummy variables)			Significant***		
VOLUME (LN)				0.110***	0.305
AGE (LN)				1.694***	1.310
PRODRATE (LN)				0.256***	0.428
INTERNALEXP				−0.028***	−.341
INDUSTRYEXP				0.029***	1.956
F change	2.426***	15.427***	1.791*	55.813***	
Total model R^2	0.127	0.192	0.221	0.556	
Adjusted R^2	0.074	0.139	0.153	0.511	
Change in R^2	0.127***	0.065***	0.030*	0.335***	

$N = 1{,}411$.
*$P<0.05$; ***$P<0.001$.

Table 6. Regression results – platform and innovation variables impact on learning in complex sub-systems

	Model 1a	Model 1b	Model 1c	Model 1d	Standardized β coefficients
Controls					
MODELYEAR (23 dummy variables)	Significant***				
REGION (two dummy variables)		Significant***			
SEGMENT (eight dummy variables)			Significant***		
VOLUME (LN)				0.236***	0.383
AGE (LN)				1.175***	0.534
PRODRATE (LN)				0.308***	0.303
INTERNALEXP				−0.017	−0.122
INDUSTRYEXP				0.010*	0.413
F change	1.257	24.576***	.410	7.661***	
Total model R^2	0.072	0.180	0.187	0.266	
Adjusted R^2	0.015	0.125	0.114	0.188	
Change in R^2	0.072	0.108***	0.007	0.078***	

$N = 1{,}411$.
*$P<0.05$; ***$P<0.001$.

platform was used for production (as distinct from when the platform was introduced) explains part of the differences across platforms in embodied learning. Those differences also depend on the platform's geographic *REGION* of origin – all else being equal, a product is likely to embody greater learning (be of relatively higher quality) if its platform came from Europe, highest if from Japan. Finally, the primary market *SEGMENT* of the platform also explains a small part of the variance.

Moving to the independent variables, analysis shows that as a group they explain an additional 7.8% of the variance in complex sub-systems and 33.5% in simple sub-systems.

Hypotheses 1–5 posited a positive relationship between learning and cumulative production volume, rate of production, platform age, and the industry's cumulative innovation experience. These hypotheses are supported both for complex and simple sub-systems. As we should expect, accumulating experience in production should lead to learning.

Importantly, the results go further – they suggest that production rate and time also matter, independent of cumulative production experience. A firm producing at a faster rate than its competitor appears to learn faster, and the time that has passed since a platform was introduced also fosters learning. Finally, as expected, a firm's innovation capability is bolstered by the cumulative experience possessed by the industry as a whole.

Finally, although Hypothesis 1 posited a positive relationship between a firm's internal innovation experience and learning, the analysis uncovered no meaningful relationship in the case of complex sub-systems. A significant but oddly inverse one exists in simple sub-systems.

The standardized β coefficients may shed more light on the relationships. As Table 6 shows, they imply that for complex sub-systems the relationship of a unit change in platform age (0.534) is somewhat greater than that of a unit change in cumulative production volume (0.383), rate of production (0.303), or cumulative industry platform experience (0.413).

Thus, there is an important implication for innovations characterized by complex sub-systems or components. *Ceteris paribus*, a firm with a complex innovation will accrue the benefits of learning relatively equally from (1) moving promptly into large-scale production and (2) seeking to learn from competitors. It also will accrue learning by producing at a rapid rate. Perhaps the best method to improve complex products is to focus on rapid, large-scale commercialization, and the transfer of knowledge between competitors.

As Table 5 shows, there is an equally striking implication for innovations with simpler sub-systems and components. As suggested by the standardized coefficients, the production process itself seems to offer less opportunity for learning. *Ceteris paribus*, the largest changes in learning are associated with the industry's accumulation of product innovation experience (standardized β 1.956) and with the age of the innovation (standardized β 1.310). It appears that the best way to improve relatively simple innovations is to produce them for a long time and to focus on incorporating competitors' improvements.

Finally, there were differences in the model's overall ability to explain variance in the two types of sub-systems. On the whole, the model explains 55.6% of the variance in simple sub-systems and 26.6% in complex ones.

Regarding the limitations of the empirical method and results, measurement error is likely to be a minor issue since each variable was taken directly or developed from industry-published data. Certainly, there is a loss of detail from the weighted aggregation of data from the model-level to the platform-level, and from the aggregation inherent in the factor-analysis-derived scores. Further, there is notable leptokurtosis (peakedness) at the means of the dependent data.

There are other conceptual and practical limitations as well. Modeling a firm as two processes is clearly a simplification of a much more complex reality. The distinction we draw between the product innovation process and the production process is logical but artificial. Further, the study cannot capture the specifics of on-going process and product improvements. Also, it cannot capture other sources of learning that may be important in this particular industry, such as innovation in automobile racing that is transferred into regular vehicles.

6. Conclusion

The ability to learn, and to incorporate learning into products, is a crucial element of a firm's competitiveness. By disaggregating experience-based learning and by defining a set of generalizable and measurable concepts, this study supports additional study of learning in the pursuit of richer and more generalizable models.

Experience in innovation has important implications for research on learning. First, the significance a firm attaches to the innovation process influences (wittingly or unwittingly) when learning can occur. That is, a firm's choices influence the opportunities for learning in the product innovation process and in the production process. The substantial learning effects that researchers and firms have observed in production may be the results of limited innovation experience – weaknesses in product or process design may not be exposed until the production stage is reached. Second, the greater a firm's innovation experience, the less dramatic will be the learning effects in production. In fact, as a firm gains experience transferring learning *between* successive innovations, production experience may yield smaller improvements *within* new products. As Zangwill and Kantor (1998) postulate, the rate of improvement in a measure should be proportional not only to the effectiveness of management but to the amount of the metric left to improve upon. This conclusion is not empirically tested in the present paper but is an important area for future research.

Furthermore, our study suggests that component or sub-system complexity affects the locus of experience-based learning. If we make a tentative leap from the component level to the product level, this finding may moderate the traditional view that rapidly expanding production volume helps a firm learn faster than its competitors. For relatively simple components or products, a greater competitive edge may be gained by imitation (using the innovation process to apply industry knowledge). For complex ones, our results suggest that there is less pronounced variation in the impact of different sources of experience-based learning. Clearly, these are tentative ideas, but they do highlight the conclusion that learning may occur differently for different kinds of products.

Terwiesch and Bohn (2001, p. 16) believe that 'It is incorrect to treat learning as an exogenous process beyond managerial control.' We agree, and suggest that continued research in diverse settings regarding the sources and impact of experience-based learning should prove highly fruitful. Experience-based learning concepts merit expanded use in research on product innovation, commercialization, and strategic management. Given the competitive dynamics associated with innovation, researchers already are looking at production learning in various high-technology settings (e.g. Chung, 2001; Terwiesch et al., 2001; Linton and Walsh, 2004). An especially exciting challenge is how to model and assess learning in the context of high-technology and knowledge-based businesses, where products may be small or intangible, lifecycles may be much shorter, and where many learning-related factors may be substantially different than in traditional environments. However, despite such apparent differences, high-technology and knowledge-based firms have platforms and production/delivery systems for their goods and services, as do 'traditional' manufacturers.

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