An Empirical Investigation of Process Innovation and Learning in Semiconductor Manufacturing: A Life-Cycle Perspective

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Abstract

In many high-tech industries, product technology is rapidly evolving and innovation in the manufacturing process is becoming an increasingly critical requisite for firms to sustain long-term competitiveness and profitability. Unfortunately, given that firms invest billions of dollars in process-related research and development each year, the topic has received little research attention in accounting literature. To fill the gap in extent research, this study develops a learning curve model and empirically investigates the impact of production experience and investment in process innovation on manufacturing costs using a unique dataset consisting of 10 years' worth of quarterly data on five successive process generations from one of the largest semiconductor manufacturing companies in Taiwan.

I integrate life cycle considerations into the analysis and test if the impact of process innovation and production experience on cost reduction differs across the technology life cycle. The empirical results indicate that manufacturing cost is negatively associated with cumulative production volume and cumulative investment in process innovation, supporting that process innovation and production experience both are important value drivers in the semiconductor manufacturing industry. I also find that investment in process innovation has a greater impact on cost reduction in the early stage of a technology life cycle and production experience plays a more important role in the mature stage, providing new evidence on learning effects and the value of process innovation.

Keywords: *Process innovation; Learning curve; Cost reduction; Technology life cycle; Semiconductor manufacturing.*

1. Introduction

Intensified global competition, shrinking product life cycle, and diversified customer demands have triggered sustained efforts by companies to effectively develop and introduce new products into mass production. Manufacturing process innovation is as a result becoming an increasingly critical capability for product innovation, particular in high-tech industries where product technology rapidly evolves. According to research reports conducted by Taiwan's Institute for Information Industry, companies in the information and electronic industry invest a total of NT$113.1 billions in research and development per year and this is still dramatically increasing. Unfortunately, given that firms are investing highly in process innovation, the topic has received relatively less research attention in accounting literature.

For the past decade, a considerable amount of studies has examined the impact of innovation on firm performance, but they mostly focus on product innovation, largely because of the proprietary nature of necessary data. For example, Chaney et al. (1991) and Koku et al. (1997) find that the announcement of new product introduction leads to positive stock returns. Bayus et al. (2003) shows that introducing new products improves firm-wide profitability and assets' growth rate in the personal computer industry. Baybus and Putsis (1999) suggest that the number of new products introduced is positively associated with market share. Damanpour and Gopalakrishnan (2001) find that high-performing banks are usually those adopting product innovations, though Ho et al. (2005) find no obvious evidence that investment in product-related R&D has a positive impact on firm value.

Most prior studies analyze the benefits of innovation by examining the increase in revenue arising from innovation, but ignore cost savings from innovation (eg., Lee and Stone 1994; Lau 1998), which might underestimate the value of R&D spending. Previous studies generally examine R&D expenditures incurred in one year, but do not take into account the impact of cumulative investment in R&D (eg., Morbey and Reithner 1990; Lev and Sougiannis 1996; Ho et al. 2005), which might cause a biased evaluation of R&D performance. Therefore, while innovation is considered as an important driver of shareholder value (Kaplan and Norton 1996, 2001; Ittner and Larkcer 2001), our understanding of its economics is greatly constrained.

To fill the gap in current research, this study empirically investigates the impact of process innovation and production experience on cost reduction in semiconductor manufacturing by employing a learning curve model. Specifically, three research questions are examined: (1) How does the accumulation of production experience affect manufacturing costs in semiconductor manufacturing? (2) How does investment in process innovation affect manufacturing costs in semiconductor manufacturing? (3) Does the impact of process innovation and production experience on manufacturing cost differ across a technology life cycle?

Our attention is directed towards the semiconductor industry for several reasons. First, product innovation in semiconductors depends on process innovation to a greater extent than is true of many other industries, since semiconductor product innovations frequently require major changes in manufacturing processes. Second, the management of new process introduction is even more important to competitive performance in semiconductor firms than in other industries, as a new product commands a price premium for a relatively brief period, and being first to the market is important to profitability.

Empirical results from this paper offer several important implications for management accounting. First, given that resources are constrained for firms, identifying cost savings from process innovation is expected to improve resource allocation between innovation and operating activities. Second, analyzing the relation between process-related R&D spending and manufacturing costs is essential for determining where in the value chain costs can be lowered. Third, R&D spending has dramatically increased in recent years. Effective management of R&D activities is becoming the key to achieving cost advantage. Identifying cost savings from process innovation is beneficial for the management of future R&D costs and measurement of R&D performance. Finally, conventional accounting analysis treats R&D spending as an expense. Understanding cost savings from process-related R&D is expected to improve the evaluation of firm value.

The next section of this article provides a short overview of research in the learning curve and management accounting literature. Section three develops several testable empirical hypotheses concerning the influence of process innovation and production experience given manufacturing costs. Section four briefly discusses the research site and the semiconductor manufacturing technology. Section five develops a model of learning in semiconductor manufacturing, describes the sources and characteristics of the data, estimation methodology, and measures for the variables used in the analysis. Section six presents and discusses the empirical results. Section seven offers concluding comments.

2. **Literature Review**

According to innovation literature, product innovation involves developing or introducing a new product (Knight 1967; Utterback and Aberbathy 1975), and process innovation is related to the production and delivery of the outcome (Kraft 1990) supporting the creation and delivery of product innovations (Gopalakrishnan et al. 1999). Generally, product innovation increases brand awareness, customer attention, and competition isolation, thus increasing sales revenue and market share, while process innovation has a more internal focus and is primarily efficiency driven (Utterback and Abernathy 1975). It typically improves the efficiency of creating the product

(Gopalakrishnan, Bierly and Kessler 1999).

Despite process innovation being considered as contributing much to cost reduction, it is generally ignored in cost accounting research. Actually, most cost accounting studies to date focus on examining the complexity of operations impacting manufacturing overhead costs while assuming R&D spending as exogenous. For example, Foster and Gupta (1990) study the correlation between manufacturing overhead costs and complexity using data from one electronic firm. Anderson (1995) examines the impact of product mix heterogeneity on manufacturing overhead costs using data from three plants of a textile firm and finds that product mix heterogeneity is costly. Balakrishnan and Soderstrom (2000) empirically investigate the cost of system congestion using data from 225,473 maternity admissions at 30 hospitals and suggest that the cost of system congestion depends on the specifics of the process.

Learning is also neglected in most prior accounting studies. In previous studies on the learning curve, production experience is considered the major driver of learning. However, many studies find that there is considerable variation in learning rates across products (Dutton and Thomas 1984) and across manufacturers of the same product (Jarmin 1994), which suggest that cost reduction does not result solely from cumulative production. Therefore, most recent empirical research studies have searched for drivers of learning other than cumulative output (Hatch 1999).

Using plant-level data, Hacth and Mowery (1998) examine the impact of process innovation on production yield and find that the method of process transfer and the allocation of engineering resources are two additional drivers of learning in semiconductor manufacturing. Macher and Mowery (2003) indicate that manufacturing performance does not result from cumulative production alone, but rather is the product of information technology and scheduling practices. Given all this, empirical evidence in this respect by far is still quite limited. Therefore, this study can fill the gap in accounting, learning, and innovation literature by demonstrating the relation between process innovation, learning, and cost reduction.

3. Hypotheses Development

Research on the learning curve argues that experience speeds production and lower costs (Macher and Mowery 2003). Generally, production skills are believed to be related to production experience (Gruber 1992). Thus, workers perform more efficiently when they accumulate more experience. In addition, productivity improvement or cost reduction is also considered to be a consequence of a growing stock of knowledge (Dutton and Thomas 1984). Specifically, as individual workers accumulate more production experience, they can transfer previous knowledge to the new problem set and thus improve their productivity (Schilling, Vidal, Ployhart, and Marangoni 2003).

There is a considerable amount of studies examining the topic of the learning curve. Wright (1936) is one of the first to see that direct labor costs per unit fall by 20% with every doubling of cumulative output in the aircraft industry. Following Wright (1936), many subsequent studies have provided evidence on the existence of learning effects in various industries as well (eg., Zimmerman 1982; Gruber 1992, 1994; Jarmin 1994; Bohn 1995; Hatch and Reichelstein 1999).

In previous studies on the learning curve, calendar time and cumulative output are identified as explanatory variables of learning (Gruber 1992; Irwin and Klenow 1994; Hatch and Mowery 1998; Schilling, Vidal, Ployhart and Marangoni 2003). In other words, production experience either accumulates with an increase in cumulative production volume or accumulates over time. Thus, we can reasonably expect that unitmanufacturing cost not only decreases with the accumulation of production volume, but also decreases over time. Hypotheses H1a and H1b are thus developed as follows.

H1a: Manufacturing cost decreases with an increase in cumulative production volume.

H1b: Manufacturing cost decreases over time.

In addition to production experience, efforts in research and development have long been viewed in both the popular and academic literature as a key determinant and indicator of firms' technological progressiveness (Itami and Numagami 1992; Pavitt 1990; Yelle 1979; Cohen and Klepper 1996). An aggressive pursuit of process technology changes is believed to have a greater impact on cost reduction than simply focusing on increasing volume and boosting capacity utilization (Pisano and Wheelwright 1995). Adner and Levinthal (2001) also indicate that the rate of performance improvement is a function of the resources devoted to innovation. Sinclair, Klepper, and Cohen (2000) suggest that research and development itself draws upon a well-developed science and engineering knowledge base, but is not generally informed by production experience.

From its related literature, process innovation includes major process changes and minor process improvement. Minor process developments include fine-tuning equipment and improving operating procedures. Major process changes require significant capital expenditures, engineering resources, and altering the basic chemistry of the process (Pisano and Wheelwright 1995). Through major process development, a physical limit can be overcome and enables a firm to considerably improve the quality of its products or to lower production costs (Kraft 1990; Adner and Levinthal 2001). Through minor process improvement, a process can be continuously adjusted and enables a firm to improve its production efficiency. In other words, investment in process innovation helps a firm to acquire the know-how regarding the design and modification of a production process that cannot be obtained through repetitively operating the same technology.

As there is considerable variation in learning rates across products (Dutton and Thomas 1984) and across manufacturers of the same product (Jarmin 1994), the learning curve is believed to be the product of deliberate activities intended to improve yields and reduce costs, rather than the incidental by-product of production volume (Hatch and Mowery 1998). Process-related R&D is considered another driver of learning. Terwiesch and Bohn (2001) offer that learning can take place through cumulative experiences and experiments. Bohn (1995) emphasizes the importance of experimentation in learning. Hatch and Mowery (1998) indicate that engineering activities influence learning-by-doing performance. Macher and Mowery (2003) suggest that manufacturing performance improvements do not result solely from cumulative production, but rather are the product of experimentations performed by engineers who seek to discover sources of manufacturing problems and implement corrective solutions. Sinclair, Klepper, and Cohen (2000) find that engineers generally identify cost-reducing strategies and figure out how to implement them by performing R&D activities, but not just through repetitive production of one product. Therefore, we expect that increased investment in process innovation leads to greater cost reduction. Thus, the second hypothesis is developed as follows.

H2： Manufacturing cost decreases with the increase in cumulative investment in process innovation.

Regarding the impact of process innovation on cost reduction, Pisano and Wheelwright (1995) suggest that it is beneficial to conduct process development early in the commercial life of a product. Specifically, the earlier a company undertakes process development, the greater the total financial return is. Hatch and Mowery (1998) also indicate that learning in the early stage of a new manufacturing process is the result of engineering analysis of production data that enables the resolution of parametric and (to a lesser extent) particle-induced yield losses. Foster (1986) shows that the cost impact of process development decreases over time - that is, at the later stages of development, increasingly larger resource investments are required to maintain a constant rate of performance improvement.

Pisano and Wheelwright (1995) suggest that investing in process development earlier could have a major impact on the cost structure of a new product, and process development conducted earlier results in achieving a better learning curve and thus lower costs. Fritsch and Meschede (2001) also indicate that innovation is critical to improving performance in the early stage of a technology life cycle, but the rate of performance improvement decrease over the life cycle. In summary, process innovation plays a more important role in improving cost performance in the early stage of a technology life cycle.

Learning-by-doing and investment in innovative activities are believed to be complementary (Iyigun 2000). Specifically, the process of learning-by-doing alters the research and development incentives for the discovery and improvement of new technologies, and vice versa. Thus, research and development efforts are always spurred in periods immediately following the introduction and adoption of new technologies, and productivity gains from learning-by-doing are relatively low in the early stage of a life cycle. As process technologies mature, the productivity gains rise rapidly as a result of learning-by-doing with the existing technology. Therefore, we develop H3a and H3b as follows.

H3a: Cumulative investment in process innovation has a greater impact on cost reduction in the early stage of a technology life cycle.

H3b: Production experience has a greater impact on cost reduction in the mature stage of a technology life cycle.

4. Research Site

The research site is an eight-inch foundry plant owned by one of the largest semiconductor manufacturing companies in Taiwan. This company is dedicated to IC foundry services. The company does not have its own products, but offers wafer fabrication services for customers. Basic processes for wafer fabrication include oxidation, diffusion, photolithography, etching, ion implantation, and metal sputter. Those basic processes are used in an infinite number of sequences and variations to produce specific integrated circuits. Based on the functions performed, the foundry plant can be divided into several functional areas: photo, etching, diffusion, chemical vapor deposition (hereafter CVD), implant, metal and chemical mechanical polishing (hereafter CMP). Wafers are moved in lots and re-enter each area several times during the fabrication process. Wafers are typically sent to the diffusion and CVD area for adding a thin dioxide layer and a silicon nitride layer on the surface respectively. They then are moved to the photo area and the etch area to perform a pattern-transfer process.

Transferring the image from mask onto the wafer surface layer entails multi-step procedures. In the first step, the pattern on the mask is transferred onto a layer of photoresist, which is a light-sensitive material. In the second step, transferring takes place from the photoresist layer onto the wafer surface. Finally, the portion of the wafer's top layer that is not covered by the photoresist is removed in the etch area and the pattern is formed on the wafer surface. After that, wafers are sent to CVD or the diffusion area for putting specific amounts of dopants on the wafer surface. To connect devices and different layers, wafers may be sent to metal, CVD, and implant areas again to perform the metallization process (Van Zant 2000).

The semiconductor manufacturing environment is believed to be the most technologically complex and capital intensive. Generally speaking, the manufacturing of a product requires several hundred processing steps and a machine group may be utilized more than once as successive circuit layers are added. Capacity utilization is thus an important cost driver. The semiconductor industry is also subject to intensive price and product feature competition, in which the capability to develop new process technologies is very important. Therefore, improved cost and superior functionality of the integrated circuit devices that can be produced are essential. To obtain these advantages, companies in this industry spend hundreds of millions of NT dollars in research and development activities and focus on rapidly introducing new manufacturing process generations and being the early introducers. There is no exception to the research site.

Manufacturing processes are commonly defined by the width of a transistor, measured in microns. Recent generations of manufacturing process, for example, have been termed as 0.35-micron, 0.25-micron, and 0.13-micron generations. These manufacturing process generations roughly correspond to the generations of products in this industry. Greater product functionality requires denser transistors. Specifically, higher density (a smaller transistor) offers several benefits, including higher processing speed, less power to operate, and more performing functions. Moreover, higher densities also lower production costs. Actually, the dependence of cost on transistor size is usually given by an exponential relationship. Maximizing transistor density is thus the most important objective of the R&D department and the explicit strategy of manufacturing process development projects (Iansiti and West 1999).

Research and development activities in semiconductor companies aim at developing new manufacturing process generations and continuously improving existing manufacturing processes, which include creating new technological options, searching for new techniques and better methodologies for producing circuits, and refining parameters of operations. It is widely believed that experience and experimentation are the two key factors determining the performance of research and development activities (Iansiti and West 1999). Specifically, as new manufacturing process generations are introduced, they involve changes in almost all processing steps and often motivate a substantial overhaul of both process recipe and equipment.

Many process steps are neither well understood, nor easily replicated on different equipment sets or in different production facilities. Manufacturing performance therefore depends much on knowledge accumulated through experimentation and engineering analysis. As the manufacturing process gradually matures, research and development activities are still necessary for firms to improve the identification of the source of yield losses and support faster implementation of corrective solutions, because yield losses due to wafer mis-processing, parametric processing problems, or particle contamination are not readily observable to equipment operators (Macher and Mowery 2003). In addition, through repetition on the part of operators, production experience is accumulated over time and thus helps to reduce mis-operations and further improve cost performance (Hatch 1999).

5. Research Methodology

5.1 Empirical Models

The traditional model for the learning curve is first proposed in Wright (1936), who documents the relationship between productivity improvement and production experience. The relationship is described in the following equation, which is still the most widely used and accepted one (Yelle, 1979; Globerson, 1980; Belkaoui, 1986; Badiru, 1992).

$$C_n = C_1 Q^{\beta} \tag{1}$$

Here, C_n is the cost required to produce the Nth unit, C_1 is the cost required to produce the first unit, Q is the cumulative amount produced, and β represents the learning rate. After logs are taken, we have the following log-linear equation.

$$ln\ C_n = ln\ C_1 + \beta\ ln\ Q \qquad (2)$$

This formulation models cost or productivity as a function of cumulative output (autonomous learning-by–doing) alone, but actually investment in process improvement is indicated as one of the factors that induces learning and governs the rate of productivity improvement (Itami and Numagami 1992; Pavitt 1990; Yelle 1979). Therefore, the above model is adapted to embed the effect of cumulative investment in process innovation as follows.

$$C_{jt} = AQ_{jt}^{\beta} R_{jt}^{\gamma} \exp(u_{jt}) \qquad (3)$$

Term A is the constant term that represents the manufacturing cost of the first unit produced, P_{jt} is the average manufacturing cost for products of generation j in quarter t, Q_{jt} is the cumulative production volume for products of generation j up to quarter t or time elapsed since production started, R_{jt} is the cumulative investment in process innovation for products of generation j up to quarter t, β, γ indicate the learning elasticity, and u_{jt} is a serially uncorrelated and homogeneous error term. After logs are taken, we have the following equation, which provides the basis for our tests of the impact of production experience and process innovation on manufacturing cost improvement.

$$ln\ C_{jt} = ln\ A + \beta\ ln\ Q_{jt} + \gamma\ ln\ R_{jt} + u_{jt} \qquad (4)$$

To control for the impact of factors other than production experience and process innovation on manufacturing costs, we further include capacity utilization in quarter t, the process complexity of generation j, and season dummies into the equation. Therefore, the following regression is estimated.

$$ln\ C_{jt} = ln\ A + \beta\ ln\ Q_{jt} + \gamma\ ln\ R_{jt} + \alpha_1 UTIL_t + \alpha_2 COMPLEXITY_j + \sum_{i=1}^{3} k_i D_i + v_{jt} \quad (5)$$

C_{jt} is product cost per unit of generation *j* in quarter *t*;

Q_{jt} is cumulative production volume for products of generation *j* up to quarter *t* or time elapsed since production started;

R_{jt} is cumulative investment in process innovation for products of generation *j* up to quarter *t*;

$UTIL_t$ is firm-wide capacity utilization in quarter *t*;

$COMPLEXITY_j$ is the inverse of the squared process line width of process *j*;

D_i indicates season dummies.

If the first quarter of the year, then D_1 =1, elsewhere D_1 = 0;

If the second quarter of the year, then D_2 =1, elsewhere D_2 = 0;

If the third quarter of the year, then D_3 =1, elsewhere D_3 = 0;

5.2 Data Collection

The data underlying this paper are drawn from the dataset of one of the largest semiconductor manufacturing companies in Taiwan. Data items include manufacturing costs, production volumes, investment in process innovation, and other characteristics for five successive generations of process technologies over the history of these processes. Specifically, quarterly data on five generations of process technologies over 1994-2004 have been collected, which include 0.35um, 0.25um, 0.18um, 0.15um, and 0.13um.

5.3 Dependent Variables

Manufacturing cost per unit of output in period *t* is used to measure the cost performance, which includes cost of direct materials, cost of direct labor, cost of indirect materials, cost of indirect labor, depreciation for the equipment and facility, utilities and supplies.

5.4 Independent Variables

Production experience: There is a considerable amount of empirical literature on the learning curve and the cumulative number of units produced is used most often to measure production experience. However, although cumulative volume is the most common measure, a number of researchers also include cumulative time as an alternative measure (Arrow 1962; Lieberman 1984; Gruber 1992). As production experience might accumulate over time or through mass production, we employ both cumulative time and cumulative production volume as proxies for experience. Cumulative volume is constructed as the sum of wafers fabricated from the date of production to the current period. Cumulative time is designed as the time elapsed since production started, which is measured in the number of quarters.

Process innovation: In the innovation literature, most studies use R&D expenditures or patents as a proxy variable for innovation activity (Kraft 1990). Some use the amount of engineering time to measure process innovation (Hatch and Mowery 1998; Hatch and Reichelstein 1999). In this study, process innovation (denoted R_t) is constructed as the accumulative R&D spending on each process up to the current period.

5.5 Control Variables

In order to control for the differences in process complexity, capacity utilization, and seasonal variation, we include five control variables in the empirical models, which are process complexity, capacity utilization, and three season dummies. Process complexity (denoted COMPLEXITY) is constructed as the inverse of the squared process line width. Process line width is the width of the metal strips that connect the transistors. The thinner the width of the transistor is, the more complex the fabrication process and the more expensive the required equipments will be. In addition, the complexity is a non-linear increasing function of line width. Thus, we take the inverse of the squared line width to measure the process complexity.

Capacity utilization (denoted UTIL) is included to control for the impact of firm-level capacity utilization on manufacturing cost. The semiconductor manufacturing industry is one of the most capital-intensive and technologically complex industries. Facility and equipment depreciation account for more than 40% of manufacturing cost. Therefore, capacity utilization has a greater impact on unit manufacturing cost and thus needs to be controlled. As for season dummies, we include them in order to control for quarterly demand variation.

5.6 Data Analysis Method

We begin by running an OLS regression, where the log of average manufacturing cost is regressed against the process-level cumulative number of wafers fabricated and cumulative R&D expenditures on each process. As time series data are used in this study, the assumption of an uncorrelated or independent error term is violated. Ordinary regression analysis can lead to inefficient estimates of regression coefficients and result in incorrect statistical tests of the significance of parameters (Ammar et al. 2003). To correct the serial correlation problem, we use AUTOREG procedure in the SAS statistical package and a maximum likelihood estimation method is employed. This procedure accounts for the autocorrelation of the errors by augmenting the regression model with an autoregressive model for the random error as follows.

$$ln\, C_{jt} = A + \beta\, Q_{jt} + \gamma\, R_{jt} + \alpha_1 UTIL_t + \alpha_2 COMPLEXITY_j + \sum_{i=1}^{3} k_i D_i + v_{jt}$$

$$v_{jt} = \psi_1 v_{jt-1} + \psi_2 v_{jt-2} + \ldots\ldots + \psi_m v_{jt-m} + \varepsilon_{jt}$$

$$\varepsilon_{jt} \sim N(0, \sigma^2) \qquad (6)$$

The AUTOREG procedure corrects the regression estimated for autocorrelation by simultaneously estimating regression coefficients and autoregressive error model parameters.

6. Empirical Results

6.1 Descriptive Statistics and Correlations

Table 1 provides descriptive statistics for the manufacturing cost and learning variables. On average, the cumulative investment in process innovation for each process exceeds NT$3 billions, suggesting that much resources are devoted to process development and improvement in the semiconductor manufacturing industry. As for production volume, it exceeds 700,000 units. Obviously, much production experience has been accumulated and learning effects should exist if any. There are also variations in the complexity of process technologies, ranging from 8.16 to 59.17, indicating that process complexity needs to be controlled. Capacity utilization ranges from 0.41 to 1.08[1], supporting that the impact of capacity utilization on product cost should be controlled.

【Insert Table 1 about Here】

Table 2 presents correlations among all the measures. Several features are worth noting. First, capacity utilization is negatively associated with manufacturing cost and process complexity is positively associated with manufacturing cost, showing that these two factors need to be controlled for while examining the learning effects. Second, manufacturing cost is negatively associated with cumulative production volume and cumulative production time, providing preliminary evidence on learning-by-doing. Third, the correlation between process complexity and cumulative investment in process innovation is relatively large, raising concerns about multicollinearity effects in our regressions. We investigate these effects by computing VIF indices for the independent variables. The VIF indices all are less than 10, suggesting that multicollinearity is not a serious problem (Hair et al. 1998).

[1] Capacity utilization is defined as the number of wafers actually being fabricated each quarter divided by the firm's practical capacity in wafers for the quarter. Generally, 100% represents full capacity. But for practical capacity is estimated based on expected product mix and actual product mix is not always exactly the same as expected product mix, the actual number of wafers produced might sometimes exceed the practical capacity. So, capacity utilization might exceed 1.

【Insert Table 2 about Here】

6.2 Impact of Production Experience on Cost Reduction

We first examine the impact of production experience on cost reduction. The results are presented in Table 3. The same models in Table 4 use cumulative production time as the proxy for production experience. All models are estimated using the AUTOREG procedure taking a first-order correction for serial correlation. Capacity utilization and process complexity measures are included in the estimation to control for the cross-sectional differences. The estimated regression coefficients along with the number of observation and R^2 are reported in Table 3 and Table 4.

【Insert Table 3 about Here】

From Table 3, we find that each model displays high explanatory power. The coefficient on cumulative output is -0.1407 (t = -11.89) and -0.1163 (t = -7.22) in models (2) and (6), respectively. Those results indicate that manufacturing cost declines as cumulative production volume increases, which supports our first hypothesis that the cost reduction is driven by production experience. This also corroborates with findings of previous studies.

【Insert Table 4 about Here】

Using cumulative time as a proxy for production experience, we estimate the learning curve models again and investigate if manufacturing cost declines over time. Table 4 presents the results. In these two models the coefficient on cumulative time is significantly negative, indicating that manufacturing cost decreases with the accumulation of production experience. The first hypothesis is still supported. Taken together, those results support that production experience is a critical driver of learning.

6.3 Impact of Process Innovation on Cost Reduction

We next turn our attention to the impact of process innovation on cost reduction. The empirical results are presented in Table 3 and Table 4 as well. From Table 3, we find that the explanatory power of models with cumulative investment in process innovation is higher than those with a production experience measure alone, indicating that cumulative investment in process innovation has incremental contributions in explaining the variation in manufacturing cost. We also find that the coefficient on cumulative R&D spending (-0.3163) is significantly negative (t = -2.16), which suggests that manufacturing cost declines as cumulative investment in process innovation increases. This supports our second hypothesis. From Table 4, we find that the coefficient on cumulative R&D spending remains significantly negative and the results are broadly consistent with model (6) in Table 3. Taken together, these results suggest that cost reduction is not only driven by exogenous production growth (autonomous learning), but also by cumulative investment in process innovation (induced learning).

Sources of Cost Reduction across Technology Life Cycle

We further examine the third hypothesis by comparing the learning effects across the technology life cycle. In defining technology life cycle stages, we originally intend to follow previous studies (eg., Thietart and Vivas 1984) and define life cycle stages based on the market growth rate - that is, products with a market growth over a period of time exceeding a constant percentage are defined to be in the growth stage, while those under a constant percentage are defined to be in the maturity stage. However, the semiconductor manufacturing business is mainly driven by worldwide demand for memory or logic products. Hence, the market growth rate for each process technology goes up and down every four to five years. Moreover, sales for each process technology have been increasing up until now. We use time span to define the technology life cycle instead. On average, a new process is introduced into the market every two years, and so we define the early stage of the technology life cycle as the first two years of full-scale production and the mature stage after that.

Table 5 presents the results. Each model displays high explanatory. From the estimation results for model (2), we find that the coefficient for the cumulative output variable is negative and significant both for the early stage and for the mature stage. The magnitude of the coefficient for cumulative output is larger in the mature stage than in the early stage. The estimation results for model (6) are broadly consistent with model (2). The coefficient on cumulative production volume is significantly negative and the magnitude of coefficient is larger in the mature stage. This evidence offers clear support for a greater impact of cumulative production volume on cost reduction in the mature stage, indicating that production experience plays a more important role improving cost performance in the mature stage.

【Insert Table 5 about Here】

As for the impact of cumulative investment in process innovation on cost reduction across the technology life cycle, the result is also presented in Table 5. For the early stage of manufacturing, the coefficient associated with the cumulative R&D spending on process innovation is significant and has the expected (negative) sign, supporting that learning is driven through process development and improvement. For the mature stage of manufacturing, the coefficient on cumulative R&D spending is significantly positive, which suggests that learning-by-doing is not solely an exogenous by-product of growth in production volume, but is also influenced by investments in process innovation. Taken together, the results support the third hypothesis that production experience has a greater impact on cost reduction in the mature stage, and process innovation has a greater impact on cost reduction in the early stage of manufacturing.

7. Conclusions and Discussions

Using process-level data obtained from one of the largest semiconductor manufacturing companies in Taiwan, this study finds that both the accumulation of production experience and cumulative investment in process innovation have negative impacts on manufacturing costs, supporting that cost reduction not only arises from learning-by-doing, but also from investment in process innovation. Furthermore, we also find evidence that process innovation has a greater impact on cost reduction in the early stage of the technology life cycle while learning-by-doing has a greater impact on cost reduction in the mature stage of manufacturing, suggesting that the benefits of process innovation are greater as manufacturing processes are newly introduced.

These findings herein have several theoretical implications. First, in the context of semiconductor manufacturing, research and development spending is not a cost, but rather they are an investment for it contributes to reducing manufacturing cost. Therefore, as conventional accounting analysis treats R&D as an expense, this might cause the underestimation of firm value. Second, this study provides evidence on the value of process innovation. Specifically, the value of process innovation arises from cost savings in manufacturing. Thus, the value of innovation might be underestimated without considering the cost impact of R&D spending. Third, this study shows that production experience and process innovation both are negatively associated with manufacturing costs, which are generally ignored in cost accounting studies. Future studies need to take into account the differences in experience and investment in process innovation while analyzing the variation in manufacturing costs. Fourth, this study shows that the impact of process-level R&D is cumulative. Analyzing R&D spending per year therefore might not fully understand the economics of innovation activities. Finally, this study provides new evidence on learning. Previous studies on the learning curve suggest that learning results solely from cumulative production, but our findings indicate that learning is the product of production experience and investment in process innovation, consistent with the claim that learning can be induced through investment in knowledge.

Empirical analyses of this study also provide a number of managerial implications. First, cumulative time and cumulative production volume have significantly negative impacts on manufacturing costs. These results suggest that manufacturing costs are not constant over time, but instead decline over time. Thus, firms should take this factor into account while forecasting future product costs and analyzing product profitability. Second, we find that investment in R&D is beneficial for reducing manufacturing costs, which suggests that firms should consider the association between R&D cost and production cost while making resource allocation decisions and measuring R&D performance. Third, our empirical results relating the decline in manufacturing costs to cumulative investment in process innovation suggest that a firm can increase the learning effects through R&D activities. Fourth, we find that process innovation investment has a greater impact on cost reduction in the early stage of the technology life cycle, supporting that firms should invest more in process improvement as new processes are introduced. Finally, our empirical analyses indicate that production experience and R&D investment are two important drivers of firm value, which firms should focus on to attain competitive advantage.

There is one limitation of this study. As our data are collected from a single company, the basic results of the empirical analysis are driven by the specific economics of the research site and thus the generalizability and validity of the findings are inevitably constrained. However, we believe several aspects of the study’s findings are germane to other companies and other industrial settings. First, the research site is one of the largest integrated circuit suppliers in the world and thus can be representative of companies in the semiconductor manufacturing industry. Second, investment in process innovation is increasing in various industries and thus effective management of process innovation is widely emphasized. Third, the tradeoff between R&D cost and production cost are present anytime a firm makes resource allocation decisions.

To overcome the limitation, future studies need to examine the cost effect of process innovation and learning in a larger number of companies. This study has focused on the cost impact of process innovation. Operations management studies indicate that greater process innovation can also increase revenues through enhanced product functionality and reliability. Future research should investigate the economic consequence of process innovation. Furthermore, future studies might also examine drivers moderating the relationship between process innovation and cost reduction.

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Table 1. Descriptive Statistics

Variable	N	Mean	Std. Err	Median	Min	Max
Manufacturing cost (UMC)	83	115280	160036	64719	32126	1112187
Cumulative production volume (CPV)	83	775717	981640	338928	22.00000	3347088
Cumulative production time (CPT)	83	9.75904	6.04574	9.00000	1.00000	24.00000
Cumulative R&D (CRD)	83	3727438895	2391612595	3242365185	557036864	9154189977
Capacity utilization (CU)	80	0.79375	0.22536	0.82000	0.41000	1.08000
Process complexity (PC)	83	23.97510	16.64965	16.00000	8.16327	59.17160

Table 2. Correlation Matrix

	UMC	CPV	CPT	CRD	CU	PC
UMC		-0.331**	-0.430**	0.218*	-0.219+	0.635**
CPV	-0.655**		0.575**	-0.311**	-0.193+	-0.504**
CPT	-0.447**	0.781**		-0.046	-0.234*	-0.244*
CRD	0.652**	-0.107	0.117		-0.332**	0.824**
CU	-0.201+	-0.156	-0.215+	-0.316**		-0.233*
PC	0.874**	-0.508**	-0.250*	0.868**	-0.192+	

a. Pearson coefficient in the upper triangle; Spearman coefficient in the lower triangle

b. + : 10% significant level; * : 5% significant level; ** : 1% significant level

c. All correlations are based on pooled data and should be interpreted with caution.

Table 3. Learning Curve Estimates without/with Process Innovation (Production experience is measured by cumulative production volume)

Independent Variables	Predicted Sign	Equation (2)	Equation (6)
Constant	?	12.7155**	19.0347**
		(43.82)	(6.48)
Cumulative Volume	-	-0.1407**	-0.1163**
		(-11.89)	(-7.22)
Cumulative R&D	-	--	-0.3163*
			(-2.16)
Process Complexity	+	0.0252**	0.0377**
		(5.53)	(5.05)
Capacity Utilization	-	-0.4982**	-0.4940**
		(-3.34)	(-3.40)
Dummy 1	?	-0.0426	-0.0539
		(-0.94)	(-1.22)
Dummy 2	?	-0.001754	-0.0106
		(-0.04)	(-0.22)
Dummy 3	?	0.003838	0.000494
		(0.09)	(0.01)
N		80	80
Total R^2		0.9469	0.9503
Durbin-Watson Statistics		1.8158	1.8462

a. N of processes = 5.

b. N of observations = 80.

c. Values in parentheses are asymptotic t-statistics.

d. + : 10% significant level; * : 5% significant level; ** : 1% significant level.

Table 4. Learning Curve Estimates without/with Process Innovation (Production experience is measured by cumulative production time)

Independent Variables	Predicted Sign	Equation (2)	Equation (6)
Constant	?	11.7178**	24.0062**
		(41.40)	(6.71)
Cumulative Time	-	-0.4402**	-0.2666**
		(-7.80)	(-3.70)
Cumulative R&D	-	--	-0.6024**
			(-3.44)
Process Complexity	+	0.0304**	0.0524**
		(7.31)	(6.45)
Capacity Utilization	-	-0.3473+	-0.3574*
		(-1.88)	(-2.05)
Dummy 1	?	-0.0327	-0.0492
		(-0.52)	(-0.88)
Dummy 2	?	0.0137	-0.004086
		(0.20)	(-0.07)
Dummy 3	?	0.009671	0.003617
		(0.17)	(0.07)
N		80	80
Total R^2		0.9121	0.9259
Durbin-Watson Statistics		1.7923	1.8036

a. N of processes = 5.
b. N of observations = 80.
c. Values in parentheses are asymptotic t-statistics.
d. + : 10% significant level; * : 5% significant level; ** : 1% significant level

Table 5. Learning Curve Estimates without/with Process Innovation: Early Stage vs Mature Stage

Independent Variables	Predicted Sign	**EARLY** Equation (2)	**EARLY** Equation (6)	**MATURE** Equation (2)	**MATURE** Equation (6)
Constant	?	12.8273**	23.2596**	13.5192**	3.4487
		(24.07)	(5.02)	(31.08)	(1.12)
Cumulative Volume	-	-0.1433**	-0.1000**	-0.1750**	-0.1989**
		(-7.62)	(-3.94)	(-6.67)	(-7.85)
Cumulative R&D	-	--	-0.5170*	--	0.4917**
			(-2.26)		(3.23)
Process Complexity	+	0.0252**	0.0434**	0.0127**	-0.008970
		(3.67)	(3.89)	(3.55)	(-1.19)
Capacity Utilization	-	-0.6034+	-0.6457*	-0.6678**	-0.5429**
		(-1.78)	(-2.04)	(-5.24)	(-4.48)
Dummy 1	?	-0.0451	-0.1083	-0.0159	-0.0185
		(-0.47)	(-1.19)	(-0.35)	(-0.43)
Dummy 2	?	-0.0345	-0.0810	0.0436	0.0475
		(-0.31)	(-0.79)	(1.05)	(1.20)
Dummy 3	?	-0.0246	-0.0450	0.0341	0.0382
		(-0.25)	(-0.51)	(0.95)	(1.09)
N		40	40	40	40
Total R^2		0.9182	0.9310	0.9188	0.9363
Durbin-Watson Statistics		1.6866	1.6746	1.7185	1.5705

a. N of processes = 5.
b. N of observations = 80.
c. Values in parentheses are asymptotic t-statistics.
d. + : 10% significant level; * : 5% significant level; ** : 1% significant level