Learning by Doing and Plant Characteristics

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Abstract

Learning by doing, especially spillover learning, has received much attention lately in models of industry evolution and economic growth. The predictions of these models depend on the distribution of learning abilities and knowledge flows across firms and countries. However, the empirical literature provides little guidance on these issues.

In this paper, I use plant level data on a sample of entrants in SIC 38, Instruments, to examine the characteristics associated with both proprietary and spillover learning by doing. The plant level data permit tests for the relative importance of within and between firm spillovers. I include both formal knowledge, obtained through R&D expenditures, and informal knowledge, obtained through learning by doing, in a production function framework. I allow the speed of learning to vary across plants according to characteristics such as R&D intensity, wages, and the skill mix.

The results suggest that (a) “informal” knowledge, accumulated through production experience at the plant, is a much more important source of productivity growth for these plants than is “formal” knowledge gained via research and development expenditures, (b) interfirm spillovers are stronger than intrafirm spillovers, (c) the slope of the own learning curve is positively related to worker quality, (d) the slope of the spillover learning curve is positively related to the skill mix at plants, (e) neither own nor spillover learning curve slopes are related to R&D intensities. These results imply that learning by doing may be, to some extent, an endogenous phenomenon at these plants. Thus, models of industry evolution that incorporate learning by doing may need to be revised. The results are also broadly consistent with the recent growth models.

Keywords: learning by doing, productivity, spillovers.

I. INTRODUCTION

Economists have recognized that learning by doing is a significant factor in industry evolution (e.g., Spence, 1981, Jarmin, 1994 and Jovanovic and Nyarko, 1994) and an important source of economic growth (e.g., Grossman and Helpman, 1992 and Lucas, 1993). They have constructed several theories that exploit learning by doing to explain a variety of economic phenomena. Yet most empirical evidence on learning by doing is limited to showing the existence of the learning curve in various settings.

If learning by doing is to play an important role in economic modeling, more needs to be known about how knowledge generated via production experience[1] is translated into improvements in productivity. An assumption implicit in many theoretical models is that learning by doing occurs automatically. However, the slope of the learning curve (the rate at which productivity increases for each doubling of production experience) can vary significantly across firms (Jarmin, 1994). This suggests that the process of learning by doing may be more complex than is usually assumed.

Therefore, it is important to understand if and how learning curve slopes vary across plants, firms or countries and if these

[1] As opposed to that gained through more formal knowledge generating activities, such as research and development.

differences are systematically related to any observable characteristics of the plants, firms and countries involved. This information can be used to assess the accuracy of the assumptions used in the theoretical literature to date, and to suggest new approaches for the future. At present, there are only a handful of empirical studies that are available to determine the validity of the assumptions made in theoretical models.

In this paper, I extend this growing empirical literature, by examining the relationship between plant characteristics and learning by doing for a sample of plants that enter SIC major group 38, instruments. Specifically, I test four groups of hypotheses concerning learning by doing. First, I look at the relationship between the quality (as proxied by wages) of both production and non production workers and learning by doing. Second, I test for a correlation between learning and the skill mix at plants. Third, I examine the relationship between learning and R&D intensity. Finally, because I have plant level data, I look at intra vs. inter firm learning spillovers.

The rest of the paper is organized as follows. I first provide some background in section II. In section III, I outline the production function framework I adopt to examine learning by doing for a sample of entrants in SIC 38. I discuss the data in section IV. I present the empirical results in section V and conclude the paper in section VI.

II. BACKGROUND

The literature on learning by doing dates to Wright (1936). The negative (positive) relationship between costs (productivity) and experience discussed by Wright has been confirmed empirically by several subsequent authors (see Alchian, 1963, Rapping, 1965, Sheshinski, 1967 and the Boston Consulting Group, 1972). Arrow (1962) did early theoretical work on learning by doing. More recent theoretical investigations have focused on the implications of learning by doing for industry evolution and economic growth.

A. Theoretical Results

In the industrial organization literature (IO), researchers have focused on the intertemporal link that learning by doing creates between the output strategies firms employ today and the technological and competitive environment in which they operate in the future. Outcomes, in these models, depend on whether these strategies are viewed as strategic complements or strategic substitutes[2]. Strategic substitutes are likely when learning is

[2] For an example see Jarmin (1994).

proprietary (i.e., firms can appropriate all the benefits of their experience). In this case, firms have the incentive to overproduce early and invest in future cost reduction (see Spence, 1981 and Fudenberg and Tirole, 1983). By doing this, incumbent firms can exploit the learning curve to gain an absolute cost advantage over potential entrants and deter entry. However, if experience is, to some extent, a public good, the incentive to overproduce is diminished since the ability of incumbents to exploit the learning curve strategically is curtailed (see Ghemawat and Spence, 1985). That is, output strategies become more complementary the larger spillovers are relative to proprietary learning. The actual market outcome depends on the distribution of learning benefits (both proprietary and spillover) across firms.

Growth theorists have exploited learning by doing to construct models of sustained economic growth (see Stokey, 1988, Young, 1991, and Grossman and Helpman, 1992). Lucas (1993) argues that these models offer a compelling explanation for the differences in the growth rates of similarly endowed economies, such as Korea and the Philippines. Namely, by producing a “higher quality” mix of goods relative to the Phillippines, Korean workers obtain, via learning by doing, the human capital necessary to produce even better goods. This is because experience accumulated from producing older, lower quality goods spills over to the newer and higher quality goods.

The extent to which models, in both the IO and growth literatures, can be said to accurately capture the essential features of the phenomena they attempt to describe, depends upon the validity of their assumptions. Particularly important are those about spillovers. In the IO literature, the ability of firms to strategically exploit the learning curve to deter entry depends on interfirm spillovers being weak relative to proprietary learning. To generate sustained economic growth, it is necessary to assume that there are strong spillovers from older generations of goods to newer, higher quality ones.

B. Empirical Results

There is a large and growing body of empirical evidence, on the extent and nature of learning by doing in the economy, that can be used to assess the validity of the assumptions used in theoretical models. The early empirical studies, mentioned above, primarily test for the existence of learning by doing and offer little guidance in assessing the realism of recent theoretical models. Beyond detecting the presence of learning, it is important to know the relative importance of proprietary and spillover learning, the sources of spillovers, whether learning rates (both proprietary and spillover) differ across plants, firms, industries and economies and, if so, what characteristics are associated with these differences. There are a handful of recent empirical studies that address a few of these issues. For convenience, these are summarized in table 1.

Lieberman (1982, 1984) examines learning, at the product level, in the chemical processing industries. He finds that differences in learning rates across products are related to R&D and capital intensities but not to process type or the prevalence of multi-plant operations in the industry. He assumes price cost margins are constant, over time, so that he can use price, rather than cost, as his dependent variable. He gives the conditions under which price is an appropriate proxy for costs. These include that the elasticity of demand is constant over time and that experience is a pure public good. However, since he employs industry level data, he cannot directly test to see if these conditions are satisfied.

Lester and McCabe (1993) look at plant level data on commercial nuclear reactors from the U.S. and France. They use a measure of reactor unavailability as their dependent variable. Their results suggest that intrasite spillovers (most sites have multiple reactors) are stronger than intrafirm spillovers that are, in turn, stronger that interfirm spillover. They also show that spillover learning rates are faster for information flows coming from reactors of the same type and from older reactors to newer ones (i.e., intergenerational spillovers). Finally, they show that learning rates where lower for U.S. plants than for those in France. They attribute this to differences in market structure across the two countries. Namely, French reactors are owned by a state run monopoly and are much more standardized than are those in the U.S. These conditions are more conducive for strong spillover learning.

Jarmin (1994) estimates a structural model of learning in the early rayon industry. Although price is the dependent variable, the model does not impose constant price cost margins. The model also allows proprietary and spillover learning coefficients to vary by firm. The results suggest that both differed significantly across firms in the early rayon industry. The model also contains parameters that measure whether firms accounted for the strategic implications of learning by doing in making their output choices. The results suggest that rayon producers did not follow myopic strategies and considered rival reactions to their decisions.

Finally, Irwin and Klenow (1994) look at firm level data in the semiconductor industry. They also use price as the dependent variable in a model that does not impose constant price cost margins. They find no intercountry differences in spillover learning and that Japanese firms learn no faster than U.S. firms. In contrast to Lester and McCabe (1993), they find little evidence of intergenerational spillovers. Their results suggest that some assumptions made in the growth models may need to be revised.

III. MODEL

Learning by doing typically refers to the negative relationship between experience and average production costs. The most common empirical formulation is the log-linear learning curve, where the log of average cost (or some proxy, when cost data are not available) is related to the log of one or more indices of experience. Typical measures of experience include cumulative output, cumulative investment and time. Plant specific (or firm specific, depending on the unit of analysis) indices of experience capture proprietary learning by doing and industry wide indices measure spillovers.

Learning can also be viewed from a production point of view (see Rapping, 1965, Nguyen and Kokkelenberg, 1992 and Bahk and Gort, 1993). The data I employ in this paper require this approach. Thus, I include measures of experience in a Cobb-Douglas production function

$$Y_{it} = Ae^{\lambda t}K_{it}^{\alpha}L_{it}^{\beta}R_{it}^{\gamma}X_{it}^{\delta}Z_{it}^{\eta}e^{\varepsilon_{it}} \qquad \textbf{(1)}$$

where Y_{it} is value added for plant i in year t, K_{it} is the book value of capital, L_{it} is total employment and g_{it} is the error term.

Three different types of knowledge stocks are included as inputs. First, R_{it} is the stock "formal" knowledge obtained through investments in research and development (R&D). Second, X_{it} is a plant specific measure of the stock of "informal" knowledge obtained through experience. In the analysis below, I proxy this as the plant's cumulative output. Finally, Z_{it} is a measure of the "informal" knowledge obtained through the experience of other plants in same 4-digit SIC industry as plant i. All knowledge stocks in this paper are beginning of period stocks.

Following the typical practice, I rewrite equation (1) as

$$y_{it} - l_{it} = a + \lambda t + \alpha(k_{it} - l_{it}) + (\mu - 1)l_{it} + \gamma(r_{it} - l_{it}) + \delta(x_{it} - l_{it}) + \eta(z_{it} - l_{it}) + \varepsilon_{it} \quad (2)$$

where the small letters denote natural logarithms. This expression can be estimated with OLS and the coefficient on labor measures deviations form constant returns to scale.

IV. DATA

I estimate (2) with data for plants entering SIC 38, Instruments, after 1972. Entry can occur either by the birth of new plants or by plants switching from another 2 digit SIC major group. I choose to focus on entrants for two reasons. First, learning by doing is typically thought to be more important for new plants[3]. Second, because the data set I use does not contain complete histories for older plants, constructing precise own cumulative output measures for entrants only is possible.

The data for this study are taken from two sources. First, I extract annual data for plants operating in SIC major group 38, Instruments, from the Census Bureau's Longitudinal Research Database (LRD) for the years 1972 through 1988. Second, I obtain firm level data on annual research and development (R&D) expenditures from the Survey of Research and Development.

To construct the samples used in the analysis below, I place the following requirements on the plant observations from the LRD. First, plants must enter SIC 38 after 1972. The LRD does not contain a complete history of plants that existed before 1963 and annual data are not available until 1972. Therefore, to maximize the accuracy of the cumulative output measures, I examine learning at only those plants that enter after 1972. I allow plants to enter the industry either through birth or by switching industries. Although plants that enter via switching have accumulated production experience in their previous 2 digit industry, I compute cumulative output using only what plants

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[3] A number of empirical studies suggest that the benefits of learning are short lived (e.g., Bahk and Gort, 1993 and Jarmin, 1994). Thus, existing plants would be expected benefit less from learning than new plants. Existing plants may benefit from episodes of learning initiated by major capital investments or product line changes. My definition of entry includes existing plants that have dramatically changed their product mix as well as new births. Identifying major capital investments is more problematic.

produce after entering SIC 38.

Second, I require that plants be in the LRD and in SIC 38 for a minimum of two years. This is the most lenient restriction on the number of observations per plant that still ensures the plant will have at least one observation for which computing its cumulative output is possible.

From 1972 to 1988 the LRD contains 57,116 plant/year observations for 20,567 plants in SIC 38[4]. The 5,992 plants that meet the above requirements contribute 21,729 plant/year observations, over this period. When these are matched with the R&D data, the number of observations drops to 6,704.

Variable construction is described in the Appendix A. Table 2 contains summary statistics for the base sample and the R&D subsample. Note that the plants in the R&D subsample are much larger, more productive and more capital intensive than those in the base sample.

V. EMPIRICAL RESULTS

Estimates of equation (2), using these data, are provided in table 3. To estimate (2), I replace the time trend with year dummies. I also include dummies for 4-digit SIC industry and for

[4] The LRD contains 7888 and 10,193 plants in SIC 38 in 1977 and 1987, respectively.

the 9 census regions[5]. Finally, I also include dummies that control for whether plants are located in an urban (i.e., within an SMSA) or non urban area and whether they are owned by single or multi establishment firms.

A. Basic Learning Regressions.

The first two columns of table 3 contain OLS estimates for the base sample where formal stocks of knowledge, proxied by R&D stocks, are left out of the regressions. Significant learning elasticities are estimated for both own and spillover learning in the first column. The second column contains the results when constant returns to scale (CRS) is imposed. In this case, the estimated spillover elasticity is not significantly different from zero. However, as the results in column 1 show, the hypothesis of CRS is rejected in this specification.

The last four columns of table 3, contain estimates from the R&D subsample. Column 3 includes both stocks of informal knowledge, as measured by own and industry wide cumulative output, and formal knowledge, as measured by firm level stocks of R&D. The estimated own learning elasticity is still large and significant. However, the spillover learning elasticity is

[5] These are New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain and Pacific.

smaller and no longer significant[6].

Also, the estimated elasticity on the stock of firm R&D is small relative to previous studies (e.g., Griliches and Mairesse, 1984 and Hall and Mairesse, 1995). This may stem from using firm level data in plant level regressions. Namely, not all of the R&D stock of large diversified firms (which make up the bulk of firms in the R&D data) is available and/or applicable to individual plants. Thus, following Adams and Jaffe (1994) I include the number of plants owned by the firm as a measure of the relative scale of plant and firm operations to control for this problem. Unlike in Adams and Jaffe, including the number of plants owned by the parent firm in the regressions, as in columns 5 and 7 of table 3, has little effect on the estimated R&D elasticities for this sample of plants.[7]

Finally, to relate learning elasticities to the more familiar notion of learning curve slope, I use the formula, slope $= 2^b - 1$, where b is the estimated elasticity (i.e., * or 0).

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[6] To see if this is due to the specification change or to the sample used, I estimated the specification in the first column on the sample from the third. The results, given in column 4, indicate that the change in sample is responsible for the decrease in the estimated spillover elasticity.

[7] Adams and Jaffe did not limit their sample to entrants as I am, however. Its possible that productivity enhancing process R&D benefits established plants relatively more than it does new ones. Likewise, new plants producing new products are probably more likely to be the beneficiaries to product R&D. This may especially be the case in technically dynamic industries such as instruments or computers. Thus, the returns to R&D for these plants may not be seen so much through productivity increases (what I'm measuring here), but by fact that they exist at all. Unfortunately, the product detail in the LRD is not sufficient to see whether the entrants in this sample are producing adequately novel products to support this hypothesis.

This number indicates the rate that value added per worker increases when own or industry wide cumulative output doubles. For the elasticities estimated in column 5, this gives learning curve slopes of 15.8% for own learning and 7.6% for spillover learning. Rapping (1965) estimated the slope of the learning curve for World War II Liberty ships to be between 11% and 29%. Although their results are not directly comparable to mine, Lieberman (1984) and Irwin and Klenow (1994) also get estimates near 20%.

B. Plant Characteristics and Learning by Doing

In this section, I examine the relationship between the slope of the learning curve and several observable plant characteristics. These include worker quality, the skill mix and R&D intensity. If a relationship exists between these characteristics, which can to some extent be altered by plants, and the slope of the learning curve, then it is likely that plants can, at least partially, influence the rate at which they learn by doing.

Learning by doing is typically thought to occur as workers perfect their tasks or management finds better ways to organize production. If this is the case, then we may expect plants with higher quality workers to have steeper learning curves. To test this hypothesis, I proxy worker quality with wages. For each plant, I compute its average hourly production worker wage. Then, for each year, I compute the plant's relative wage by dividing its average hourly wage by the mean hourly wage for its 4-digit industry. Finally, I compute the average relative wage over all observations for each plant and use this as my plant level measure of worker quality.

In the first two columns of table 4, I estimate separate own and spillover learning elasticities for plants according to which average (relative) wage quartile plants reside[8]. The results show that plants paying, on average, higher production worker wages have significantly higher own learning elasticities than plants paying lower wages[9]. For example, from the regression in the first column we see that the slope the own learning curve ranges from 13.8% (=$2^{0.186}$-1) in the first wage quartile to 18.2% (=$2^{0.241}$-1) in the third quartile and 17.6% (=$2^{0.235}$-1) in the fourth. The patterns of the own and spillover learning curve slopes are

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[8] Namely, I estimate variants of (2) where I replace the terms $*(x_{it} - l_{it})$ and $0(z_{it} - l_{it})$ with

$$\sum_{j=1}^{4} D_j \delta_j (x_{it} - l_{it}) \ and \ \sum_{j=1}^{4} D_j \eta_j (z_{it} - l_{it}),$$

respectively, where D_j is a dummy for the jth wage quartile.

[9] For regression in the first column of table 4 the Wald statistic for the hypothesis that all plants have the same own learning elasticity is $P^2(3)$ = 11.31 which is significant at the 5% level. A similar test for the regression in the second column yields a test statistic of $P^2(3)$ = 12.16 which is significant at the 1% level. The hypothesis that plants in the four production worker wage quartiles have the same spillover elasticity can not be rejected at standard levels of significance for either of the regressions in the first two columns.

summarized in panel (a) of figure 1. The positive relationship between the slope of the own learning curve and production worker quality is even stronger in second column regression where plants in the highest wage quartile have an own learning curve slope of 22.6% compared with 13.1% for plants in the lowest quartile. This coupled with the fact that plants that pay higher wages tend to be larger and, therefore, gain production experience faster implies that high wage plants receive significantly more benefits from plant specific learning by doing than do lower wage plants. On the other hand, while there is a statistically and economically significant relationship between production worker quality, as proxied by wages, and own learning, there is no significant relationship between spillover learning and worker quality at these plants.

The finding that production worker quality is positively associated with proprietary learning by doing is consistent with the notion that own learning occurs as workers perfect their tasks. The first two regressions, in table 4, show that higher quality production workers perfect their tasks more quickly than do lower quality workers.

In the last two columns of table 4, I estimate similar regressions for non production worker wages. The LRD does not contain data for hours worked by non production workers. Therefore, the quartiles in these regressions refer to average relative annual non production worker wages. The hypothesis of equal own learning elasticities can be rejected for both non production worker specifications[10]. However, as panel (b) of figure 1 shows, the pattern is less clear than in the production worker case. Nevertheless, it appears that the ability of plants to learn from their own production experience is positively related to the quality of both its production and non-production workers. Worker quality does not, however, appear to be related to the ability of plants to learn from spillovers.

In addition to its quality, the composition of the plant's workforce may affect how the plant learns from both its own and spillover experience. In particular, plants with a higher proportion of skilled workers may be more able to benefit from learning, all else equal.

In table 5, I examine the effect of the skill mix on a plant's ability to learn by doing. A plant's skill mix is proxied by its share of non production workers to total employment[11]. The higher this number, the more skilled is the plant's workforce. The patterns of the estimates across the skill mix quartiles suggest that plant's using more skilled workers have lower own learning coefficients and higher spillover

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[10] The Wald statistics are $P^2(3) = 18.47$ and $P^2(3) = 10.05$ for the specifications in columns 3 and 4, respectively.

[11] This is an admittedly crude measure but it the best one available in the LRD. It has been used with some success by Bernard and Jensen (1996) and Dunne, Haltiwanger and Troske (1996).

coefficients. This result makes sense if one believes that knowledge, even informal knowledge, generated outside the plant requires more skilled workers to make it applicable to the plant's operations. However, this pattern is statistically significant[12] for the regression in the first column only. These results are depicted in panel (a) of figure 2.

Finally, as in Lieberman (1984), I examine the relationship between R&D and the slope of the learning curve. He found that more R&D intensive industries had steeper learning curves. To my knowledge, this relationship has not been tested at the plant or firm level. In table 6, I perform a similar exercise as I did tables 4 and 5. To classify plants according to R&D intensity, I compute the average R&D intensity of their parent firm over the plant's tenure in the LRD.

Again, I estimate separate own and spillover learning elasticities for each average R&D intensity quartile. The results indicate that there is no significant difference in either own or spillover learning elasticities across R&D

[12] In the first column of table 5, the hypothesis of equal own learning elasticities across the skill mix quartiles is not rejected with Wald statistic of P^2 (3) = 3.70, however the hypothesis that the own learning coefficients for the highest and lowest quartiles are equal can be rejected at the 10% level (P^2 (1) = 2.74). The hypothesis of qual spillover coefficients across the skill mix quartiles is rejected at the 1% level with a Wald statistic of P^2 (3) = 14.31. Neither the equal own or equal spillover learning hypotheses can be rejected even at the 10% level for the regression in column of table 5.

intensity quartiles for these plants. The results from the first column regression in table 6, are shown in panel (b) of figure 2 that highlights the lack of a relationship between R&D intensity and either own or spillover learning by doing. Thus, the correlation, between R&D intensity and the slope of the learning curve, that Lieberman found in product level data for the chemical industry does not appear in these plant level data for SIC 38.

C. Inter vs. Intrafirm Spillovers

As mentioned above, the study by Lester and McCabe (1993) is the only one that compares intra and interfirm spillovers. The nuclear power industry is rather unique, however, and it would be interesting to see if their results hold up for different industries. Table 7 presents estimates from regressions that examine this issue.

The sample used for the regression in the first column is restricted to those plants owned by firms that have at least two plants in a given 4-digit industry within SIC 38. This regression contains estimates of own and both intra and interfirm spillovers. The results suggest that, for the sample of plants examined here, intrafirm spillovers are quite small compared with interfirm spillovers[13]. This result runs counter to intuition that suggests that plants should benefit more from the experience of other plants owned by the same parent firm. It is also contrary to the results Lester and McCabe found for nuclear reactors.

The second column contains estimates where I include firm and industry level stocks of experience only (where “firm” includes all plants in a 4-digit industry owned by the firm). Note that, even when firm experience includes the plant, the coefficient on own firm experience is less than a third as large as the own plant experience coefficient from the first column.

The results in table 7 provide additional evidence that the learning curve is not an effective tool for entry deterrence. Not only are there spillovers, but these spillovers tend to be stronger across plants belonging to different firms than they are across plants within the firm.

VI. Conclusions

In this paper, I examined the relationship between several plant characteristics and learning by doing. I employed a data set consisting of plants that entered SIC major group 38,

[13] The statistical significance of this result is marginal, however. A Wald test for the equality of the intra and interfirm spillover elasticities is significant at only the 10.4% level (P^2 (1) = 2.64). But the result is economically significant with the interfirm spillover elasticity being 62.5 times the magnitude of the intrafirm spillover elasticity.

instruments, after 1972. I tested several hypotheses concerning the relationship between observable plant characteristics and learning by doing. The results suggest that (a) “informal” knowledge, accumulated through production experience at the plant, is a much more important source of productivity growth for these plants than is “formal” knowledge gained via R&D expenditures, (b) interfirm spillovers are stronger than intrafirm spillovers, © the slope of the own learning curve is positively related to worker quality, (d) the slope of the spillover learning curve is positively related to the skill mix at plants, and (e) neither own nor spillover learning curve slopes are related to R&D intensities.

These results have important implications for economic models incorporating learning by doing. First, the finding that interfirm spillovers are stronger than intrafirm spillovers adds to the evidence that the learning curve is an ineffective tool for entry deterrence. Second, to the extent that plants and firms can control the quality and skill mix of their workforces, the finding that learning curve slopes are related to worker quality and the skill mix suggests that learning curve slopes are endogenous. That is, not only can plants control their rate of productivity growth by changing the rate at which they accumulate experience, but they can alter the rate at which equal increments in the stock of experience increase productivity. This suggests that we may need much richer models of industry evolution in cases where learning by doing is considered.

Finally, the findings on worker quality and the skill mix are consistent with the recent growth models. These models suggest that, by working near the limit of their knowledge, high quality workers continually learn the skills necessary to produce even more complex goods and services and that this process leads to sustained economic growth. Further, they provide an explanation for why countries with lower skilled workforces have a difficult time catching up with the higher skilled developed countries. The results in this paper provide evidence, at the mirco level, that higher skilled workers are those that learn the most.

Table 1
Summary of Recent Studies

Paper	Industry	Unit of Observation	Dependent variable	Experience Indices	Spillover Sources	Learning curve slope allowed to vary
Lieberman (1984)	Chemicals	Product	Price (constant margins)	Cumulative Output, Time	Industry Wide	by R&D intensity, capital intensity, industry concentration, and multi-plant operations
Lester and McCabe (1993)	Nuclear Power	Reactor (plant)	Reactor Availability	Reactor Age	Intra-site, Intra-firm, Inter-firm	by vintage, reactor class, vendor and country
Jarmin (1994)	Rayon	Firm	Price (variable margins)	Cumulative Output	Inter-firm	by firm
Irwin and Klenow (1994)	Semi - conductors	Firm	Price (variable margins)	Cumulative Output	Inter-firm (both within and across countries), intergeneration	by country and chip generation

Table 2
Summary Statistics

	Large Sample Mean	R&D Subsample Mean
Number of Observation	21,729	6,704
Number of Plants	5,992	1,383
First Year	79.7	79.6
Last Year	85.5	85.0
Tenure	5.8	5.4
Observations per Plant	3.6	4.9
Employment, 1987	114	331
VA/L, 1987	57,346	66,394
K/L, 1987	26,468	30,442
X/L, 1987	560,904	724,787
Z/L, 1987 (in millions)	10,855	4,653
R&D/L, 1987	-	14,403,638
plant share, 1987	-	0.197

Notes: First Year is the first year in which the plant is observed in SIC 38 in the LRD. Last Year is the last year up to 1988 for which the plant is observed in SIC 38 in the LRD. Tenure is (First Year) - (Last Year). Observations per plant are the number of times the plants are actually observed in the LRD over the 1972-1988 period. VA/L is value added per employee. K/L is the capital/labor ratio. X/L is the plant specific stock of experience per worker. Z/L is the stock of (4-digit) industry wide experience net of X per worker. R&D/L is the stock of R&D per worker and plant share is the ratio of plant for firm shipments for plants owned by R&D performing firms. Further details on variable sources and construction are available in Appendix A.

Table 3: Basic Learning Regressions
Dependent variable: log(VA/L)
(Absolute t-statistics in parentheses)

	1	2	3	4	5	6	7
log(L)	0.183* (3.578)		0.138 (1.632)	0.119 (1.389)	0.136 (1.613)		
log(K/L)	0.138* (16.450)	0.137* (16.387)	0.104* (6.663)	0.111* (6.912)	0.104* (6.666)	0.103* (6.620)	0.103* (6.624)
log(X/L)	0.211* (22.358)	0.210* (22.288)	0.211* (13.912)	0.219* (14.379)	0.211* (13.877)	0.210* (13.894)	0.210* (13.859)
log(Z/L)	0.176* (3.465)	-0.005 (0.987)	0.108 (1.288)	0.104 (1.230)	0.105 (1.257)	-0.028* (-3.225)	-0.029* (-3.241)
log(R/L)			0.034* (8.405)		0.036* (6.351)	0.034* (8.320)	0.036* (6.299)
log(# of plants)					0.005 (0.438)		0.005 (0.435)
R^2	0.243	0.242	0.220	0.211	0.221	0.220	0.220
N	11,905	11,905	5,026	5,206	5,024	5,026	5,024

Notes: All regressions also include a constant, year dummies, 4-digit SIC dummies, region dummies and dummies for whether the plant is located in an urban area and whether it is owned by a multi plant firm.
* denotes significant at the 1% level.

Table 4
The Effects of Production and Non-Production Worker Wages on Learning
(Absolute t-Statistics in Parentheses)

		Production Workers		Non-Production Workers	
		1	2	3	4
log(L)		0.205* (4.037)	0.123 (1.454)	0.198* (3.883)	0.134 (1.564)
log(K/L)		0.128* (15.377)	0.094* (6.150)	0.130* (15.394)	0.096* (6.108)
log(R&D)			0.033* (5.995)		0.032* (5.602)
log(# of plants)			0.001 (0.107)		0.001 (0.062)
log(X/L) by average wage quartile	Q1	0.186* (13.634)	0.177* (9.351)	0.185* (13.650)	0.180* (8.904)
	Q2	0.205* (13.650)	0.204* (10.927)	0.202* (13.942)	0.199* (9.162)
	Q3	0.241* (13.612)	0.273* (7.851)	0.258* (17.644)	0.261* (11.423)
	Q4	0.235* (15.384)	0.294* (7.331)	0.258* (17.562)	0.253* (3.931)
log(Z/L) by average wage quartile	Q1	0.186* (3.699)	0.095 (1.151)	0.184* (3.644)	0.108 (1.295)
	Q2	0.188* (3.742)	0.096 (1.165)	0.186* (3.658)	0.110 (1.310)
	Q3	0.179* (3.528)	0.074 (0.883)	0.168* (3.294)	0.090 (1.068)

	Q4	0.182* (3.613)	0.063 (0.740)	0.186* (3.668)	0.085 (0.993)
R^2		0.253	0.235	0.247	0.227
N		11,901	5021	11,803	4994

Notes: All regressions also include a constant, year dummies, 4-digit SIC dummies, region dummies and dummies for whether the plant in an urban area and whether it is owned by a multi plant firm.
* denotes significant at the 1% level.

Table 5
The Effect of the Skill Mix in Learning
(Absolute t-statistics in parentheses)

log(L)		0.171* (3.339)	0.135 (1.560)
log(K/L)		0.133* (15.926)	0.099* (6.420)
log(R&D/L)			0.035* (6.253)
log(# of plants)			0.005 (0.478)
log(X/L) by Skill Quartile	Q1	0.220* (15.500)	0.231* (9.751)
	Q2	0.219* (14.371)	0.222* (8.513)
	Q3	0.202* (12.903)	0.197* (7.469)
	Q4	0.191* (13.246)	0.200* (8.638)
log(Z/L) by Skill Quartile	Q1	0.156* (3.081)	0.089 (1.068)
	Q2	0.162* (3.161)	0.095 (1.110)
	Q3	0.171* (3.350)	0.106 (1.247)
	Q4	0.181* (3.517)	0.107 (1.250)
R^2		0.249	0.221
N		11,905	5010

Notes: All regressions also include a constant, year dummies, 4-digit SIC dummies, region dummies and dummies for whether the plant in an urban area and whether it is owned by a multi plant firm.
* denotes significant at the 1% level.

Table 6
The Effect of R&D Intensity on Learning
(Absolute t-Statistics in Parentheses)

log(L)		0.181^{**} (2.493)	0.153^{***} (1.791)
log(K/L)		0.108^{*} (7.617)	0.104^{*} (6.500)
log(R&D)			0.024^{*} (3.157)
log(# of plants)			-0.001 (0.096)
log(X/L) by R&D Quartile	Q1	0.191^{*} (9.898)	0.197^{*} (8.221)
	Q2	0.204^{*} (9.528)	0.197^{*} (8.176)
	Q3	0.265^{*} (11.370)	0.252^{*} (9.744)
	Q4	0.185^{*} (8.361)	0.180^{*} (7.467)
log(Z/L) by R&D Quartile	Q1	0.167^{**} (2.320)	0.129 (1.530)
	Q2	0.166^{**} (2.316)	0.130 (1.548)
	Q3	0.149^{**} (2.028)	0.113 (1.326)
	Q4	0.180^{**} (2.476)	0.141^{***} (1.666)
R^2		0.211	0.224
N		6167	4945

Notes: All regressions also include a constant, year dummies, 4-digit SIC dummies, region dummies and dummies for whether the plant in an urban area and whether it is owned by a multi plant firm.
* denotes significant at the 1% level.
** denotes significant at the 5% level.
*** denotes significant at the 10% level.

Table 7
Intra vs Interfirm Spillovers
(Absolute t-Statistics in Parentheses)

log(L)	0.132*** (1.736)	0.146** (2.333)	0.165*** (1.646)
log(K/L)	0.119* (8.658)	0.123* (10.532)	0.105* (5.871)
log(R/L)			0.038* (5.246)
log(# of plants)			0.015 (1.118)
log(X/L)	0.182* (13.781)		0.189* (11.133)
log(F/L)		0.054* (10.414)	
log((F-X)/L)	0.002** (2.274)		0.0002 (0.175)
log((Z-F)/L)	0.125*** (1.645)	0.131** (2.113)	0.115 (1.188)
R^2	0.205	0.154	0.212
N	5451	8335	3689

Notes: All regressions also include a constant, year dummies, 4-digit SIC dummies, region dummies and dummies for whether the plant in an urban area.
* denotes significant at the 1% level.
** denotes significant at the 5% level.
*** denotes significant at the 10% level.

Figure 1

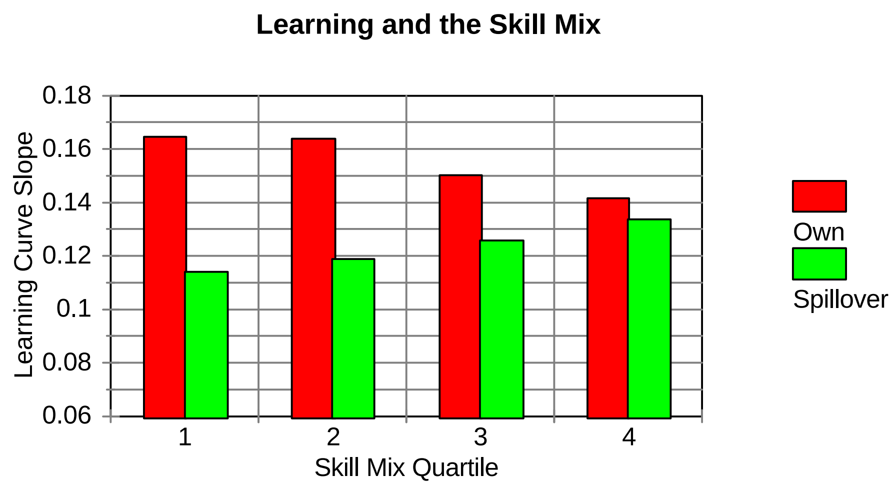
Learning and Production Worker Quality
0.2
0.18
0.16
0.14
0.12
0.1
0.08
Learning Curve Slope
1
2
3
4
Production Worker Wage Quartile
Own
Spillover

(a)

Learning and Non Production Worker Quality
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
Learning Curve Slope
1
2
3
4
Non Production Worker Wage Quartiles
Own
Spillover

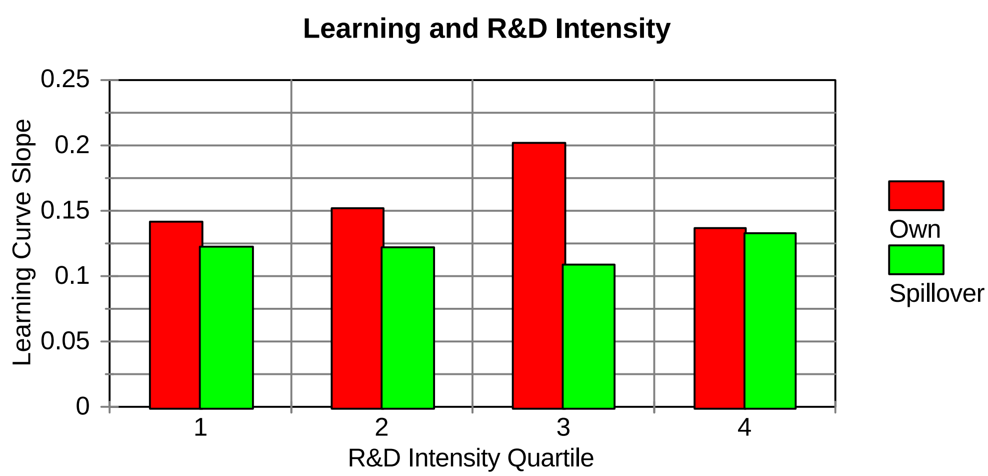
(b)

Figure 2



Learning and the Skill Mix
Learning Curve Slope
0.18
0.16
0.14
0.12
0.1
0.08
0.06
1
2
3
4
Skill Mix Quartile
Own
Spillover

(a)



Learning and R&D Intensity
Learning Curve Slope
0.25
0.2
0.15
0.1
0.05
0
1
2
3
4
R&D Intensity Quartile
Own
Spillover

(b)

APPENDIX A

This appendix describes derivation of some of the variables used in the paper.

Value added is deflated using the 4-digit SIC deflators from the NBER Productivity Database (see Bartelsman and Gray, 1995).

Capital is the book value of machinery and structures assets deflated by BEA's 2-digit capital stock deflators.

R&D Stock is computed for each firm as $R_{jt} = (1-*)R_{jt-1}+r_{jt-1}$ where R_{jt} is the R&D stock for firm j in year t and r_{jt} is firm j's R&D expenditures in period t. These stocks are computed using the total R&D figure reported in the NSF R&D Survey. I use the commonly applied 15% depreciation rate for R&D stocks (see Hall and Mairesse, 1995).

Own Cumulative Output is computed as $X_{is} = X_{is-1} + .5(q_{is}+q_{is-1})(year_s-year_{s-1}-1) + q_{is-1}$, where X_{is} is cumulative output for the s^{th} observation of plant i, q_{is} is real output and $year_s$ is the year in which the s^{th} observation occurs. Real output is computed as the total value of shipments adjusted for changes in inventories and deflated with the NBER 4-digit deflators. This measure tries to account for the fact the we do not observe many plants in LRD annually. Most smaller plants are in the LRD once every five years, corresponding to the Census of Manufactures. I, therefore, impute the change in cumulative output for these smaller plants

Industry Cumulative Output is computed as $Z_{jt} =Z_{it-1} + Q_{jt-1}$ where Z_{jt} is cumulative industry output in period t and Q_{jt} is real output for the j^{th} 4-digit industry in period t. Industry output is given by $Q_{jt} = \sum_{i\in j}(w_{it}q_{it})$ for $t\neq$ (72, 77, 82, 88) and $Q_{jt} = \sum_{i\in j}(q_{it})$ for t= (72, 77, 82, 88), where w_{it} is a survey weight that is inversely proportional to the plants probability of being sampled in the Annual Survey of Manufactures (ASM).

APPENDIX B. Econometric Issues

There are a number of econometric issues to consider in estimating models such as (2). First, it may be inappropriate to view some of the right hand side variables, such as labor, as exogenous. Solutions to this problem include using instrumental variables (IV) or estimating a multi equation structural model. I do not have sufficient data to estimate a structural model so I present IV estimates in table A.1. I use lagged values of employment, capital per worker and knowledge stocks, in addition to the exogenous dummy variables, as instruments. The results indicate that the IV estimates do not differ greatly from the OLS estimates.

Another potential problem is that the right hand side variables may be correlated with unobserved plant characteristics and OLS estimates of (2) are biased. If these unobserved plant characteristics are fixed over time, one can eliminate them in panel data by differencing. Table A.2 contains results from several difference regressions. The results in the first two columns show that first differencing reduces the magnitude of the capital coefficient relative to the levels estimates in table 3. Also, the estimated own learning coefficients have the wrong sign. While first differencing may sweep out plant fixed effects, it may also increase the impact of measurement error (see Griliches and Hausman, 1986). This may explain the large and significant negative returns to scale coefficient.

One way to get around this is to use longer differences. I report estimates from third difference regressions in the final four columns of table A.2. They appear more reasonable than the first difference results in that the own learning coefficients are no longer negative. However, although they are closer to zero than in the first difference regressions, the returns to scale coefficients still indicate significant decreasing returns to scale. This suggests that measurement error may still be a problem[14].

Employing instrumental variables or differencing reduces the number of observations available for estimation. Further, it is not clear that these methods yield better estimates. I often use either restricted samples or estimate separate learning coefficients for different subgroups of plants. Difference or IV

[14] Taking longer differences may eliminate this problem but it reduces the sample even more severely.

estimation methods would impose severe restrictions on the number of observations available for these regressions. Therefore, I estimate all of the regressions, in the paper, in levels to take advantage of the largest number of observations possible.

Table A.1
Instrumental Variable Estimates
(Absolute t-Statistics in Parentheses)

	OLS		IV	
log(L)	0.233** (2.149)		0.267 (1.179)	
log(K/L)	0.082* (4.190)	0.082* (4.172)	0.102* (4.416)	0.101* (4.354)
log(X/L)	0.311* (14.767)	0.310 (14.734)	0.284 (13.454)	0.281 (13.375)
log(Z/L)	0.183*** (1.745)	-0.041** (2.101)	0.241 (1.071)	-0.024 (1.164)
log(R/L)	0.030* (4.297)	0.028* (4.007)	0.035* (4.707)	0.035* (4.719)
log(# of plants)	-0.002 (0.149)	-0.040 (0.019)	-0.003 (0.216)	-0.003 (0.202)
R^2	0.250	0.249	0.248	0.247

Notes: N=3503. All regressions also include a constant, year dummies, 4-digit SIC dummies, region dummies and dummies for whether the plant in an urban area and whether it is owned by a multi plant firm. Instruments include all the exogenous dummy variables plus lagged values for capital, R&D, own and industry wide experience and log(# of plants) of firm shipments.
* denotes significant at the 1% level.
** denotes significant at the 5% level.
*** denotes significant at the 10% level.

Table A.2
Difference Estimates
(Absolute t-Statistics in Parentheses)

	First Differences				Third Differences			
constant	0.059* (4.857)	0.0001 (0.013)	0.075* (4.023)	0.043* (2.694)	0.037 (1.535)	-0.051** (2.341)	0.087** (2.451)	0.024 (0.758)
log(L)	-0.355* (6.539)		-0.343* (2.708)		-0.217* (5.567)		-0.264* (3.306)	
log(K/L)	0.042** (2.573)	0.067* (3.982)	0.042 (1.447)	0.051*** (1.704)	0.041** (2.260)	0.052* (2.779)	0.042 (1.413)	0.053*** (1.726)
log(X/L)	-0.134* (4.661)	-0.042*** (1.647)	-0.156* (3.617)	-0.122* (3.136)	0.022 (0.936)	0.065* (2.652)	0.009 (0.281)	0.028 (0.832)
log(Z/L)	0.014 (0.522)	0.157 (5.675)	-0.046 (1.172)	0.029 (0.692)	0.010 (0.404)	0.114* (4.844)	-0.038 (0.782)	0.037 (0.801)
log(R/L)			0.007 (0.288)	0.064* (2.730)			0.006 (0.375)	0.043** (2.457)

log(# of plants)			0.039 (0.612)	0.163* (3.340)			0.013 (0.379)	0.102* (3.153)
R^2	0.032	0.019	0.027	0.021	0.040	0.030	0.039	0.032
N	7147	7147	3315	3315	3470	3470	1683	1683

* denotes significant at the 1% level.
** denotes significant at the 5% level.
*** denotes significant at the 10% level.

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