*LEARNING AND THE SOURCES OF CORPORATE GROWTH**

Paul Geroski,
London Business School

Mariana Mazzucato,
Open University

June, 2001

preliminary draft: please do not cite without the permission of the authors; comments are most welcome.

*We are obliged to the ESRC for financial support, and to Franco Malerba and seminar participants at Bocconi University for helpful comments on an earlier draft. the usual disclaimer applies.

Correspondence:

Geroski: London Business School, Sussex Place, Regents Park, United Kingdom NW1 4SA, tel. 00-44-207-262-5050, fax. 00-44-207-402-0718, pgeroski@lbs.ac.uk
Mazzucato: Economics, Open University, Walton Hall, Milton Keynes, United Kingdom, MK7 6AA, tel. 00-44-1908-659191, fax. 00-44-1908-654488, m.mazzucato@open.ac.uk

ABSTRACT

This paper explores the link between learning and corporate growth by developing different models of learning and showing that they produce observably different models of corporate growth. Using data on the growth of a number of firms in the US Automobile industry during the 20th century, we compare these different models of growth in an effort to identify the major sources of learning which these firms seem to rely on. Although there are interesting differences between growth processes pre and post the Second War, the basic conclusion that we are drawn to is that learning in this sector is largely unsystematic and opportunistic.

JEL Classification: L1 Market Structure, Firm Strategy, and Market Performance,
03 Technological Change.

I. INTRODUCTION

Most people regard knowledge as a key source of competitive advantage and, therefore, of corporate performance. As a consequence, a large literature has grown up over the past decade around the subject of corporate learning. Much of it is concerned with how learning occurs, how knowledge is retained within the firm and how learning affects the strategy and structure of a firm's operations. This literature carries a strong normative presumption that learning is a good thing for a firm to do. The problem is that the evidence that we have on the link between learning and corporate performance is sketchy. This is, of course, no surprise, as neither learning nor the stock of knowledge that it presumably creates is directly observable. Much of what we do know about the effect of learning on corporate performance comes from work that uses expenditures on R&D or patenting as proxies for knowledge accumulation. While this is better than nothing, these are, at best, very limited measures of the totality of learning which firms might benefit from. Nevertheless, to the extent that these proxies measure learning, this literature suggests that learning does indeed stimulate corporate growth, profitability and productivity.

This paper takes a somewhat different approach to the problem of identifying the link between learning and corporate performance. Rather than using one or more imperfect proxies for corporate learning to explain performance, we start from the premise that both the process of learning, and the stock of knowledge that it creates, is wholly unobservable. What is observable, however, are the consequences of learning. What is more – and this is the key to our approach – different types of learning (or, different learning mechanisms) have different implications for the times series behaviour of the observable consequences of learning, namely corporate performance (and, in particular, corporate growth). It follows, then, that one ought to be able to infer something about the nature of the learning which a firm does from observations about it's performance.

We follow the lead of the R&D literature and posit a relationship between the stock of knowledge possessed by a firm and it's output. We then distinguish five different types of learning, and show that each produces a distinctive time path for output. After reviewing some recent literature on firm learning in Section II, we will outline these models in Section III. Although these different models of learning are not nested, it turns out that they all reduce to a common, baseline specification which emerges from a model in which learning is wholly unsystematic and opportunistic, and we will take this to be our null hypothesis. In Section IV, we apply these five models to firm level data drawn from 85 years of the US automobile industry. We conclude in Section V with a few observations on future directions for research of this type.

II. LEARNING AND CORPORATE PERFORMANCE

The simplest and most familiar story about learning is that which has been built up around "learning by doing" and the learning curve.[1] In this story, firms accumulate experience through production and generate a stock of knowledge which is proportional to their cumulative output. If corporate performance is driven by this stock of knowledge then performance differences between firms should be fairly stable over time (since differences in cumulative output will not change much once firms are very well established). It is usually argued that because learning is essentially an investment in a very specific product and associated production process, firms should pursue learning curve strategies only when consumer tastes or the technological environment is relatively stable. When it's market is turbulent, firms are more likely to gain competitive advantage by pursuing strategies that focus on exploring and creating new product variants (instead of investing even more existing ones). Amongst other things, this suggests that firms pursuing learning curve strategies are likely to lose market share in periods of turbulence, but will outperform others when their market environment is stable and their customers are price sensitive.

The business literature on core-competencies and the evolutionary literature on innovation has pushed the idea of corporate learning well beyond the notion that learning occurs as a simple "by-product" of doing.[2] The evolutionary view focuses on the variety of different ways that firms can learn and how this learning is tied to different sources of knowledge and technological capabilities, both of which may be embedded in organisational structures (e.g. US Tayloristic vs. Japanese 'Ohnistic'). In this way of thinking, learning evolves over time through the development of specific capabilities and costly investments in "absorptive capacity".[3] Whatever their source, these capabilities are widely regarded as being difficult to imitate, and certainly this is true for a competence like "absorptive capacity". It is not surprise to discover, therefore, that this view of learning has developed, in part, to explain persistent intra-industry but inter-firm differences in performance, something which is typically observed when one examines accounting profitability. The fact that a firm's absorptive capacity is likely to depend on its prior knowledge means that in this view learning is *path-dependent*: those firms that have developed a significant body of knowledge will be better learners and hence develop more knowledge in the future. This is not dissimilar to the learning by doing story, except that experiential learning is typically narrower than learning through investments in R&D (etc). The diversity of a firm's knowledge gained though production and research is important since it increases the chances that the new information which arrives possibly by happenstance can be understood and interpreted creatively. Hence, "absorptive capacity" is a result, or by-product, of the firm's active engagement in learning activities: it is both a cause and a consequence of learning.

A number of studies have linked different types of learning to different organisational and industry environments, arguing that learning in different environments results in different technological trajectories which then affect future learning patterns:

> *"A first broad property is the diversity of learning modes and sources of knowledge across technologies and across sectors. For example, in some activities knowledge is accumulated primarily via informal mechanisms of learning by doing and learning by interacting with customers, suppliers, etc. In others, it involves much more formalised activities of search (such as those undertaken in R&D labs). In some fields, knowledge is mostly generated internally and specific to particular applications. In others it draws more directly upon academic research and scientific advances. Recent research suggests that this diversity of learning modes may be a major determinant of the diverse patterns of evolution in industrial structures (e.g. in terms of distribution of firm sizes, natality and mortality of firms, corporate diversification*)."[4]

Observations like this often yield a classification of different types of learning, including: learning by doing, learning by using, learning from advances in science and technology, learning from inter-industry spillovers, learning by interacting, and learning by searching (this list is taken from Malerba, 1992). Depending on which sector that we are examining., some of these are internal to firm's production process or use of products, while others are external to the firm and are related to the development of science or the actions of its competitors. Needless to say, some of these sources of learning generate knowledge that is easy to protect, and to the extent that this is true, they are likely to lead to long term performance differences between firms.

Rich and insightful as this literature undoubtedly is, it provides only very modest guidance for empirical work. The two strongest implications of this literature are that: learning is likely to be firm and/or sector specific, and that it is likely to lead to persistent differences in corporate performance. This, unfortunately, does not take us very far. In particular, persistent differences in performance are not necessarily permanent, and that means that it is important to learn as much about how much firms forget as about how (and how much) they learn; understanding competence destruction is as important as competence enhancement if we are to understand the performance of particular firms over time.[5] Further, it is one thing to argue that there are important firm differences in learning or in the stock of competencies maintained by different firms in different sectors, and quite another to associate these differences with observable differences in corporate performance. It is, therefore, important to move beyond the "*how*" and "*why*" of corporate learning, and address the question of "*so what*?". That is our goal in this paper.

III. OBSERVABLE IMPLICATIONS OF DIFFERENT LEARNING PROCESSES

We start with the presumption that learning, and the stock of knowledge which results from it, are wholly unobservable. What can be observed, however, is the consequences of learning, and we focus here on output. We posit the existence of a "knowledge production function" which links the stock of knowledge possessed by firm i at time t, KN(t), with it's output, Q(t):

$$Q(t) = A(t)KN(t)^{\alpha} \tag{1}$$

where A(t) summarizes the effects of all other inputs (and anything else) on output rates. Taking logs and first differencing,

(2) $$\Delta\log Q(t) = \Delta\log A(t) + \alpha\, \Delta\log KN(t).$$

Since the rate of growth of KN(t) is, by definition, the rate of learning, it follows immediately that the rate of growth of the firm will vary directly with the rate of learning. For future reference, we use LE(t) to denote the rate of growth of KN; i.e. $LE(t) \equiv \Delta\log KN(t)$. Further, for expositional ease, we will, for the time being, suppose that $\Delta\log A(t) \equiv \varepsilon(t)$, a white noise error process.

Equations (1) and (2) suggests that corporate performance measured by the current rate of growth of the firm is a signal of the current rate of learning. The quality of that signal evidently depends on two things: α, the elasticity of output with respect to knowledge, and the inherent variability in A(t). One simple observation that one can make from this is that the performance of firms in high technology sectors where learning really matters and which are insulated from macroeconomic and other shocks will be more informative about their learning than might be the case in more traditional, cyclically sensitive sectors. A more substantive observation, though, is that cross firm comparisons of learning using this approach are likely to be most informative for a sample of firms with a similar α and a similar variance in A(t); i.e. for firms in the same sector. A third observation is that any inferences about learning that one makes using (1) or (2) are, of course, conditional on how allowance is made for other factors, A(t).

The production function approach apparently underlying equation (1) appears at first sight to be rather restrictive, or at least mechanistic, and it is important to note that the basic relationship revealed in (1) emerges from almost all output choice models typically used in the theory of the firm literature. A firm that maximizes profits will choose an output rate which depends on it’s marginal costs and some parameters of demand, and, since these parameters are affected by learning, it follows that there will be a relationship between the stock of knowledge and output rates.[6] Even if this relationship is very complex, (1) can be regarded as a first order approximation to the true relationship between output and those cost or demand parameters affected by learning, and it is, therefore, unlikely to paint an terribly inaccurate picture of how learning affects corporate performance (except, perhaps, in being overly simple).

The real problem with (1) or (2) is that neither KN(t) nor the rate of learning, LE(t), are directly observable. However, different types of learning will induce different time paths in KN(t), and so in Q(t). It follows, then, that observing movements in Q(t) over time may cast useful light on the time path of KN(t) and so on the rate of learning. We distinguish five different types of learning process:

(i) unsystematic learning

The simplest story of all about learning is that which says that firms learn things in a wholly unstructured, unsystematic sort of way, opportunistically absorbing whatever their environment (randomly) throws up and, just as likely, forgetting what they have learned previously. In this case,

$$LE(t) = \xi(t), \tag{3}$$

where $\xi(t)$ is an i.i.d. random variable with mean zero and a variance which is constant (or at least so long as the environment which generates the learning opportunities to which the firm passively responds is constant over time). In this case, it follows that

$$\Delta \log Q(t) = \varepsilon(t) + \xi(t) \equiv \nu(t), \tag{4}$$

meaning that firm size follows a random walk. This is, of course, exactly the state of affairs described by Gibrat's Law, and we take it as our null hypothesis in what follows.[7]

(ii) learning by innovation

The basic idea of a learning by innovation story is that virtually all learning can be tied to the appearance of particular product or process innovations.[8] One can think of this in one of two ways: either these innovations embody all the learning that firms actually do, or they act as a signal that intensive (but unobserved) learning has occurred and, amongst other things, has produced the particular innovation in question. Either way, the presumption is that relatively little learning occurs between innovations, so that observing the realization of an innovation is tantamount to observing the act of learning. If I(t) is a count of major product or process innovations which are introduced by firm i at time t, then this story might be modelled as

$$(5) \qquad LE(t) = \beta I(t) + \xi(t)$$

where $\beta > 0$. It follows, then, that

$$(6) \qquad \Delta \log Q(t) = \alpha\beta I(t) + \nu(t),$$

meaning that output follows a random walk with a trend driven by the stochastic arrival of particular innovations.[9]

There are many ways that one can make the specification in (5) richer and possibly more realistic. If major innovations have long lasting effects on performance, or if their short run effect is much smaller than their long run effect, then (6) might be generalized to

$$(7) \qquad \Delta \log Q(t) = \alpha\beta(L)I(t) + \nu(t),$$

where $\beta(L)$ is a polynomial in the lag operator L. Similarly, one might generalize (6) by allowing the effects of particular innovations to be firm specific, or to depend on the number of previous innovations that the firm has produced (allowing for some kind of differential ability to use new innovations).

(iii) spillovers

It is, of course, very likely that firms will learn from their rivals, so that learning occurs largely as a result of imitation between firms. There is a well established tradition of modelling spillovers in the patents and R&D literature, and it is one of two routes that we propose to follow here.[10] To avoid notational clutter, we continue to suppress the i subscript which identifies firm i, but we will use a j subscript to identify variables associated with any or all of i's rivals. If the effects of innovative activity spillover between firms, then (6) becomes

(8) $$\Delta \log Q(t) = \alpha\beta I(t) + \alpha\beta_j I_j(t) + \nu(t),$$

where β_j measures the effect that rivals innovations, $I_j(t)$, have on the performance of firm i.

There are several problems with (8) as a way of capturing spillovers, but the most serious is that it presumes that all spillovers are associated with observable innovations. It is more than possible that some or all of the entire stock of knowledge, $KN_j(t)$, possessed by firm j might spillover to i. If we suppose that this occurs with at least a one period lag, then (1) becomes

(9) $$\Delta \log LE(t) = \alpha_j \Delta \log KN_j(t-1) + \xi(t),$$

which yields a relationship between the growth rate of firm i in period t and that of it's rivals in t-1,

(10) $$\Delta \log Q(t) = \lambda_j \Delta \log Q_j(t-1) + \nu(t),$$

where $\lambda = \alpha\alpha_j$. Equation (10) embodies the fact that a high degree of inter-firm spillovers is likely to lead to a convergence in growth rates and, possibly in the long run, firm size.[11]

(iv) learning by doing

As we noted earlier, the classic source of learning is experiential, and it underlies the famous "learning curve" much beloved of corporate strategists. Although there are many ways to think about "experience", most accounts focus on cumulative production, $X(t) \equiv \Sigma_t\, Q(\tau)$, as the main driver of experience and, therefore, of learning,

$$\text{(11)} \qquad LE(t) = \phi \log X(t) + \xi(t),$$

so that

$$\text{(12)} \qquad \Delta \log Q(t) = \alpha\phi \log X(t) + \nu(t).$$

In passing, it is worth noting that this specification can be enriched in at least two ways (which we will not pursue here). In the first place, learning may spillover between firms, and so the performance of firm i may depend not only on it's own cumulative output, but also more generally on the experience of some or all of it's rivals (this will be particularly the case if some or all of the industry is geographically concentrated). This will create a link between the growth rates of individual firms and cumulative industry output. Second, one might allow knowledge to be forgotten or to become obsolescent. One very simple way to do this is to define the stock of experience as $X(t) \equiv Q(t) + \Sigma_\tau\, \rho^\tau Q(\tau)$, where $0 < \rho < 1$ is a depreciation factor which describes the rate at which experience is forgotten. This effectively turns (12) into

$$\text{(13)} \qquad \Delta \log Q(t) = \phi \log Q(t) + \phi \log \{1 + \Sigma\rho^{t-\tau} Q(t-\tau)/Q(t)\} + \nu(t),$$

where the middle term on the right hand side of (13) is effectively a weighted average of the rate of growth of firm i in previous years.

(v) learning built on internal resources

None of the learning mechanisms thus refer to any limit or constraint on the ability of firms to learn. In fact, most of us believe that there are constraints on the ability of a firm to learn, and that these depend on a set of capabilities usually referred to as "absorptive capacity". In addition, there may also be constraints on the speed with which firms accumulate knowledge (analogous to Penrose effects). Both of these observations effectively mean that the rate of growth of the stock of knowledge of the firm is likely to depend on it's level and recent increase. Further, it is generally believed that there may be increasing returns to knowledge; i.e. that knowledge gained today facilitates the acquisition of further knowledge tomorrow. This too will create a link between the stock of knowledge maintained by a firm today and tomorrow. Either way, it seems reasonable to believe that learning might depend on

$$(14) \qquad LE(t) = \delta \log KN(t-1) + \theta LE(t-1) + \xi(t),$$

which means that

$$(15) \qquad \Delta \log Q(t) = \rho \log Q(t-1) + \psi \Delta \log Q(t-1) + \mu(t),$$

where $\mu(t) = \varepsilon(t) + \alpha\theta\varepsilon(t-1) + \alpha\delta \log A(t-1)$, $\rho = \alpha^2\delta$ and $\varphi = \alpha\theta$.

Equation (14) is a specification which is familiar from a large empirical literature on the growth of firms (see the references in footnote 7 above). The most common version of (14) used in that literature sets $\varphi = 0$ and generates estimates of ρ, interpreting it as a measure of the degree of "*reversion to the mean*" (or, in more modern parlance, "*convergence*"). Equation (14) gives one way of thinking about how reversion to the mean occurs. The parameter δ reflects the effects of absorptive capacity. If $\delta > 0$ (which, of course, implies that $\rho > 0$), then learning is easier the larger is the current stock of knowledge possessed by the firm; i.e. increasing returns to knowledge accumulation prevails. If, on the other hand, $\delta < 0$ (i.e. $\rho < 0$), then diminishing returns prevail (and, indeed, knowledge will gradually depreciate over time). When $\delta > 0$ knowledge and, therefore, size differences between firms become magnified over time; when $\delta < 0$, firms eventually converge. $\theta < 0$ (or, equivalently, $\psi < 0$) indicates the existence of diminishing returns to growth, and may, therefore, reflect limitations on the ability of firms to absorb knowledge over time. If, on the other hand, $\theta > 0$ (or, equivalently, $\psi > 0$), then firms will display sustained period of high (or low) growth.[12]

IV. GROWTH PATTERNS IN THE US AUTOMOBILE INDUSTRY

Our goal in what follows is to use these several different models of learning to try to identify the major sources of corporate growth for firms. Since it seems reasonable to believe that learning occurs in different ways in different sectors, we have drawn our sample of firms from a single industry – the US automobile industry. As learning is typically taken to lead to persistent performance differences between firms, we have collected as long a times series of data as possible to enable us to measure just how long persistent performance differences exist. Finally, as it seems plain that different environments (possibly including different stages of the industry life cycle) may lead to different types of learning or lead to different consequences of learning on corporate performance, we have tried to collect data across at least two quite different competitive regimes for our sample: the pre-War period (1910-1941) and the post-War period (1949-1998).

the data

Our data covers the period 1910-1998 for the US automobile industry. The firms (and time periods) included in our sample are shown on Table I. Although quite a number of US and foreign owned firms have operated in this industry over the years, we limit our investigation to those for which enough times series data was available to make sensible computations (needless to say, they are also the ones with the most significant market shares). We also test the model for all firms together (a "firm" that we will refer to as "*total*", which was present for the years 1910-1998). There are only two observables in the models outlined in Section III: the output rate of each firm in each year and the number of innovations they produced in each year.[13]

Figure I displays total industry output from 1910-1998, while Figure II shows the annual growth rate of total industry output over the period (omitting the War years). Figure III plots the total number of innovations produced in each year (up to 1981, when our innovation data ends). It seems clear that there are two rather different periods which can be distinguished in the data: the pre-War (1910-1941) and the post-War (1949-1998) periods.[14] Indeed, the (second) War generates a "natural" break in the data, since car production in the US ceased for those several years. This division separates an earlier period in which the industry faced quite a lot of turbulence from changes in technology and demand from a later one where both tastes and technology were, arguably, more stable. The pre-War period saw the establishment of the industry, while the post-War period saw it rise to dominate the US economy and then mature. Growth rates in the early period were higher but much more erratic than they were in the later period, when growth was (relatively) steady and sustained. Data for foreign firms is only available for the post-War period since they produced only a minuscule fraction of total industry output before the War. Entry by foreign firms eventually led to a noticeable decline in the incumbents' (i.e. major US owned automobile manufacturer's) market shares and a sharp rise in industry advertising[15]. Finally, innovative activity gradually declined over the whole history of the industry, although Figure III shows very little evidence of the sample break that seems so plain in Figures I and II.

Table II shows the mean and the standard deviation of the growth rates for all the domestic and foreign firms individually, and for all firms taken together. It also shows the *p*-values from the Shapiro-Wilks test for normality. As we saw on Figure II, the market as a whole grew more slowly after the War than before, but the interesting observation is that all of the individual firms in our sample (except Chrysler) experienced a higher average growth rates in the pre-War period than post-War. This relatively rapid post-War growth for individual firms in a market that was growing more slowly came at the expense of the many smaller firms who populated the market in the pre-War period and then exited after the War. The pre-War period is also characterised by a higher variance in growth rates for both those individual firms who operated in both periods, and for the market as a whole. Some of the foreign owned firms in our sample have average growth rates post-War that are similar to, or higher than, those recorded by the Big 3 firms in the pre-War period (Honda, Toyota Mitsubishi); VW and Mazda, however, had negative average growth rates (????). The distribution of growth rates is, on the whole, normal (the exceptions are Packard, Studebaker, Honda and Toyota).

Table III shows the correlations between the growth rates of different firms in the two periods (the post-War period is further divided into pre and post-1965 periods so that the growth of the foreign firms can be compared with those of the Big 3 more readily). What is interesting about these correlations is that, with the exception of the Big 3, they are rather small. That is, variations in the growth rates of most of the firms who operate in what is apparently the same market are rather low. Ford, GM and Chrysler all seem to expand and contract pretty much together, but other US and foreign firms displayed much more idiosyncratic patterns of growth. One might argue that this is evidence that competition within the Big 3 is much higher than it is between members of the Big 3 and the rest or within the rest, or one might argue that they operate in different market segments or belong to different strategic groups.

Table IV shows the correlations between current and recent past growth rates for each firm. Although these correlations are slightly higher in the post-War period than in the pre-War period, the simple fact is that they are all very small (Honda and, to a lesser degree, Toyota and Nissan are exceptions to this observation). The obvious conclusion is that is that high (or, for that matter, low) growth rates simply do not persist for long over time; that is, that firms do not, on the whole, enjoy long periods of sustained success (or failure). This, of course, implies, that performance differences between firms are unlikely to persist for long either.

regression results

We now turn to the five different models of learning discussed in Section III .These are described in equations (6) and (7) ("learning by innovation"), (8) ("innovation spillovers"), (10) ("knowledge spillovers unrelated to specific innovations"), (120 ("learning by doing"), (15) ("internal resources") and, finally, (4) (the null hypothesis of "unsystematic learning"). We estimated each equation for each firm first in the pre-War period (1910-1944) and then in the post-War period (1946-1999). In each case, the independent variable is the growth rate of units produced by each firm or group of firms, measured as the first difference of the log of firm size. We examined each of the models independently, and then we explored fuller specifications combining several of the simple models into a more complete regression containing all or most of the relevant independent variables.

To test the (6) or (7), the learning by innovation hypothesis, we regressed the growth rate of units produced by each firm against the number of innovations that it produced lagged (with up to three lags). Regressions were not run for firms that produced no innovations (we did regress the total innovations produced by all firms against aggregate industry growth rate). Since the innovation series ends in 1981, our post-War results contain only 36 years instead of 53. The results do not provide much, if any, support the view that the production of innovations is an important or systematic driver of growth rates. The signs on the co-efficients on innovations in most of the regressions were often negative on the first lag and positive on the second and third lags; the co-efficients were positive more often in the pre-War period than in the post-War period.

Equation (8) explores the effects of innovation spillovers on growth by regressing the growth of each firm on as the number of innovations produced by the rest of the industry (with up to three lags included) . These net industry innovation terms were almost always insignificant, and, indeed, combining (7) and (8) -- that is, including both own and rivals innovations up to three lags as possible determinants of growth rates – produced regressions whose explanatory power was weak (in most cases the F-test suggested that <u>all</u> the included innovation variables could be excluded from the regressions). It is hard to avoid the conclusion that innovative activity -- own or rivals – has not been a substantial or a systematic driver of corporate growth in this sector.

To explore the role of general knowledge spillovers as a source of growth -- equation (10) -- we regress the rate of growth of output for each firm on growth rate of total output (lagged once) of all other firms taken individually or collectively. Amongst the Big 3 firms, output related spillovers are significant only for Ford (in both the pre-War and post-War periods) and for Chrysler (only in the pre-War period). In both cases, the effect is negative, which is difficult to interpret as a learning effect (or, for that matter, as an agglomeration effect). The effect of spillovers is very strong on the growth of most of the other US firms only during the post-War period, but the estimated effect is negative (and significant).

Spillovers are positive and significant determinants of the growth of most of the foreign firms (who are present only in the post-War period). All in all, however, these regressions do not provide much in the way of support for the view that output related spillovers power growth. This is, of course, consistent with the weak correlations between the growth rates of different firms displayed on Table III.

To test the learning by doing relationship we regress the firm's growth rate of output on the log of it's cumulative output (lagged one period). Amongst the Big 3, learning by doing was a significant driver of growth rates only for Ford, for which it was *positive* and very strong in the pre-war period. Learning by doing also had a significant effect on the growth of almost all of the small domestic and foreign owned firms in the post-War period, but with a *negative* (it was insignificant for VW, Mazda and Mitsubishi).

Thus, we have found very little substantive or systematic evidence to suggest that that the production of innovations, spillovers or learning by doing are important sources of growth for firms in this industry. This leaves us with the notion "learning through internal resources" -- equation (15) --, and the null hypothesis that learning is unsystematic – equation (4).

The argument that absorptive capacity conditions learning builds on the observation that firms who accumulate a significant body of knowledge will be better learners, and hence will be able to accumulate knowledge more rapidly or thoroughly in the future. Onwe implication of this is that learning is liable to be path-dependent because prior knowledge permits the assimilation and exploitation of new knowledge: success today creates the conditions for success tomorrow. The result, as equation (15) shows, is that growth rates will be autocorrelated over time. One easy way to examine the hypothesis of learning by absorptive capacity is to regress firm growth rates on previous growth rates. However, as we saw on Table IV, growth rates are not highly correlated, and this is confirmed by simple regressions of current on lagged growth rates. The effect of prior growth rates on current growth rate is usually much larger in the post-War period than in the pre-War period, and, in fact, none of the pre-War coefficients are significant.

Equation (15) leads one to a regression of current growth on lagged size and lagged growth. Table V shows the estimates that we obtained from this regression. In general, the estimates suggest that $\varphi = 0$, but that $\rho < 0$. This is not consistent with the view that there are increasing returns to knowledge accumulation (it suggests that knowledge depreciates) or that there are increasing returns to growth. In fact, the F statistics shown on Table V indicate that it is, in general, difficult not to arrive at the conclusion that all of the co-efficients in all of the regressions shown on the Table are jointly zero. This is also true for virtually all of the regression results that we have discussed in this paper, and that leaves one with precious little evidence upon which to build a case for rejecting the null hypothesis that learning is unsystematic and opportunistic. Indeed, whatever it is that powered the growth of the firms in this industry, it does not seem to have produced a systematic or sustained pattern of performance over time.

VI. CONCLUSION

If learning is an important source of competitive advantage, then firms who accumulate skills and knowledge appropriate to their environment will outperform those who do not. More interesting and possibly more useful is a second insight, namely that the way that firms learn ought to be visible in how they perform. In this paper, we have used this second insight to pursue the empirical implications of five different methods of learning on corporate growth performance in the US automobile industry in the pre and post-War periods. The bottom line is this: although one can detect traces of most of the different learning mechanisms in the data, it is hard to find any systematic evidence which supports any hypothesis other than that which asserts that learning is unsystematic and random.

In a sense, all of this is not surprising. There is a long and rich literature which suggests that corporate growth rates are, roughly speaking, random, and that is basically what we have observed. The various models that we have set out in this paper have enabled us to interpret this result in terms of different learning processes.[16] The surprise, we think, comes from the fact that most theorizing by those interested in the causes or consequences of corporate learning area effectively seeks to explain a set of stylized facts about corporate performance based on accounting profits data which are simply not robust. Studies of accounting profits typically find long lasting performance differences between firms, and profits are typically persistently high or low over time for particular firms. There are lots of reasons why this might be that have nothing to do with the accumulation of distinctive and long lasting skills and knowledge. There are also other measures of corporate performance that do not display these properties – corporate growth rates amongst them. Since it seems possible to draw entirely different conclusions about learning, and about the nature of skill and knowledge accumulation by firms, from two different but commonly accepted measures of corporate performance, one is entitled ask whether there might be a better way forward.

Figure I: Total Industry Output

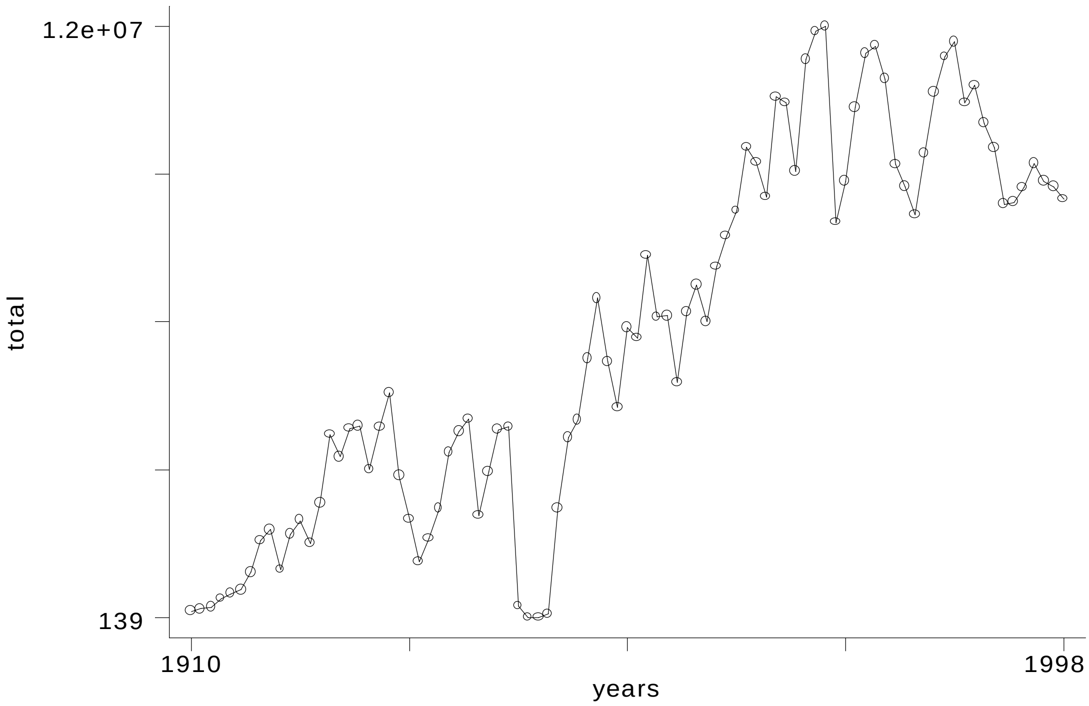

Figure II: The Rate of Growth of Industry Output

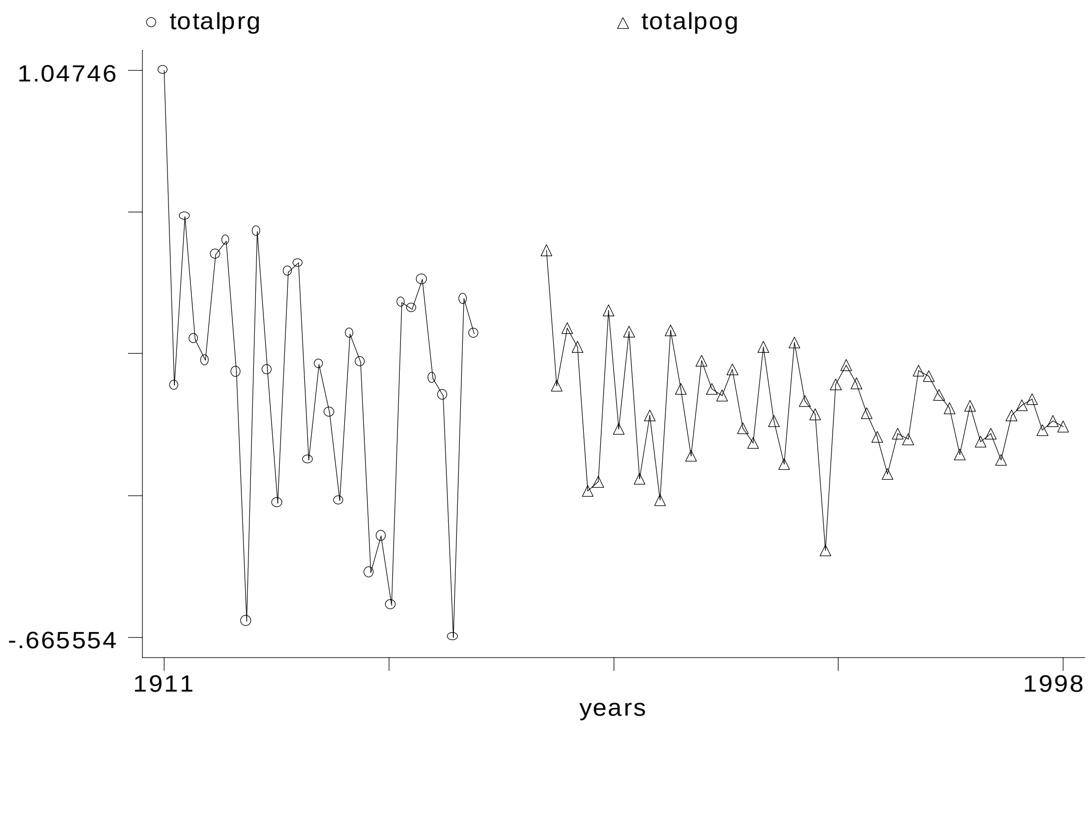

Figure III: The Total Number of Innovations Produced

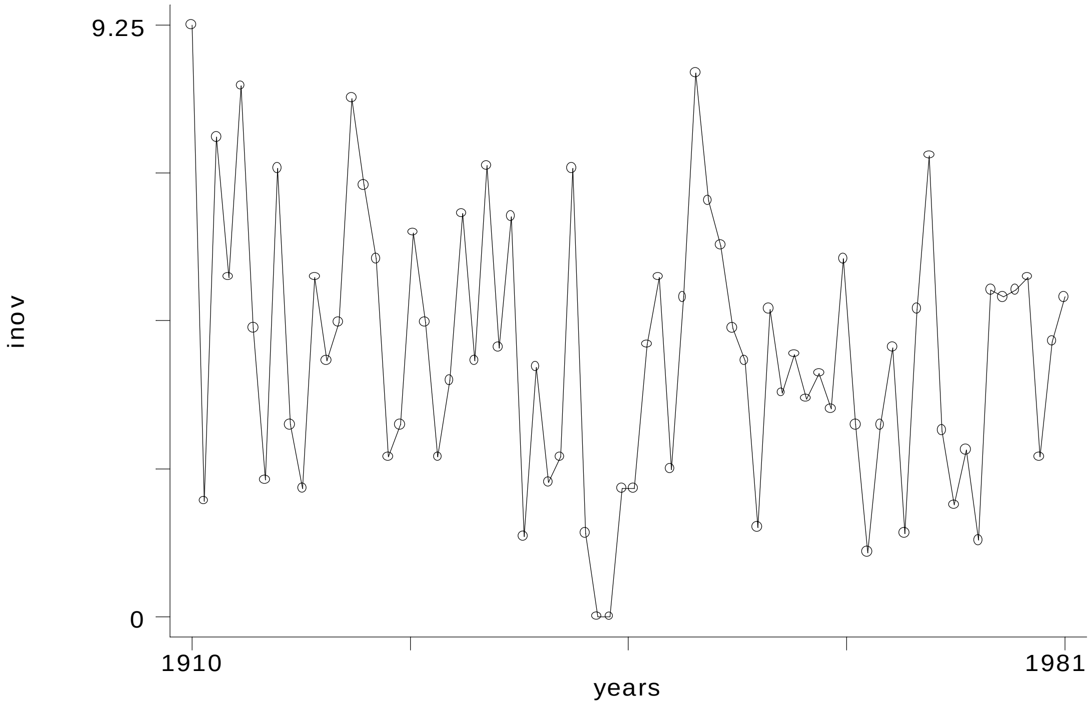

Table I: The Firms and Sample Periods

Big 3 firms:

GM	1910-1998
Ford	1910-1998
Chrysler	1925-1998

Other US owned firms:

Packard*	1910-1941
American	1946-1985
Studebaker	1946-1966

Foreign owned firms:

VW	1965-1998
Honda	1971-1998
Nissan	1965-1998
Toyota	1996-1998
Mazda	1985-1998
Mitsubishi	1985-1998

* There is no output data for Packard for the period 1926 – 1934

Table II: Descriptive Statistics: Corporate Growth Rates

	Mean pre	Mean pst	St.Dv pre	St. Dv pst	Norm pre	Norm pst
GM	0.1244	0.0109	0.3857	0.1853	0.51407	0.5109
Ford	0.0994	0.0172	0.536	0.1946	0.2402	0.2268
Chrysler	0.1271	-0.0002	0.3411	0.4415	0.2597	0
Packard	0.194		0.5899		**0.0102**	
Stud		-0.2632		0.7078		**0.0345**
AMC		0.0045		0.249		0.3052
VW		-0.011		0.2518		0.5751
Honda		0.1643		0.2321		**0.0002**
Toyota		0.1209		0.2289		**0.0001**
Mazda		-0.0095		0.1253		0.7457
Mitsubishi		0.0838		0.1896		0.1249
TOTAL	0.1312	0.0169	0.3947	0.1484	0.2276	0.9259

Col. 1-2: Mean and standard deviation of firm growth rates.
Col. 3-4: Shapiro-Wilk test for normality on growth rates (**bold** values indicate that can reject the null hypothesis that the variables are normally distributed).

Table III: Correlations in Growth Rates across Firms

Pre-War

	Gm	Ford	Chrysler	Packard
Gm	1			
Ford	0.7969	1		
Chrysler	0.9899	0.7798	1	
Packard	0.6737	0.7878	0.6562	1
Total	-0.0021	-0.179	0.0087	0.1264

1949-1964

	Gm	Ford	Chrysler	Studeb	AMC
Gm	1				
Ford	0.8981	1			
Chrysler	0.5881	0.5384	1		
Studeb	0.4419	0.3392	0.2695	1	
AMC	0.0923	-0.0073	0.166	0.5721	1
Total	-0.0981	-0.1406	-0.165	-0.4309	-0.3221

Post-1965

	Gm	Ford	Chrysler	VW	Nissan	Honda	Toyota	Mazda	Mitsub.
Gm	1								
Ford	0.471	1							
Chrysler	0.6588	0.6839	1						
VW	0.2513	-0.0174	0.0439	1					
Nissan	0.2788	0.3462	0.2622	-0.1401	1				
Honda	0.0951	0.0337	-0.0032	0.328	-0.2638	1			
Toyota	0.3227	0.0388	-0.0708	0.3299	-0.4165	0.5039	1		
Mazda	0.4198	0.5717	0.2886	-0.0782	-0.0955	0.0835	0.2442	1	
Mitsubishi	-0.2954	-0.1264	-0.4229	-0.2069	0.2715	0.059	0.142	0.0135	1
Total	-0.1219	-0.2036	0.0066	0.2362	0.394	0.3218	-0.2113	-0.4386	0.1362

Table IV: Autocorrelations in growth

	PRE-WAR				**POST-WAR**				**POST-WAR**		
	GM	GM(t-1)	GM(t-2)		GM	GM(t-1)	GM(t-2)		VW	VW(t-1)	VW(t-2)
GM	1			GM	1			VW	1		
GM(t-1)	-0.0308	1		GM(t-1)	-0.1149	1		VW(t-1)	0.1184	1	
GM(t-2)	0.0481	-0.0746	1	GM(t-2)	-0.2434	-0.1599	1	VW(t-2)	0.1818	0.1172	1
GM(t-3)	-0.3052	0.0394	0.0192	GM(t-3)	0.053	-0.247	-0.0692	VW(t-3)	-0.3452	0.1497	0.1146

	FD	FD(t-1)	FD(t-2)		FD	FD(t-1)	FD(t-2)		NIS	NIS(t-1)	NIS(t-2)
FD	1			FD	1			NIS	1		
FD(t-1)	-0.0154	1		FD(t-1)	-0.0158	1		NIS(t-1)	0.3415	1	
FD(t-2)	-0.1967	-0.0435	1	FD(t-2)	-0.148	-0.2274	1	NIS(t-2)	0.3102	0.3316	1
FD(t-3)	-0.0006	-0.1972	0.1661	FD(t-3)	0.1754	-0.1361	-0.0044	NIS(t-3)	0.2077	0.2639	0.4164

	CH	CH(t-1)	CH(t-2)		CH	CH(t-1)	CH(t-2)		HON	HON(t-1)	HON(t-2)
CH	1			CH	1			HON	1		
CH(t-1)	0.0522	1		CH(t-1)	-0.4399	1		HON(t-1)	0.5678	1	
CH(t-2)	-0.2844	-0.2113	1	CH(t-2)	-0.0556	0.1202	1	HON(t-2)	0.6584	0.5724	1
CH(t-3)	-0.3154	-0.3536	0.1578	CH(t-3)	-0.0093	-0.0555	-0.3019	HON(t-3)	0.6364	0.6256	0.623

	PAC	PAC(t-1)	PAC(t-2)		STU	STU(t-1)	STU(t-2)		TOY	TOY(t-1)	TOY(t-2)
PAC	1			STU	1			TOY	1		
PAC(t-1)	-0.3413	1		STU(t-1)	-0.2281	1		TOY(t-1)	0.4988	1	
PAC(t-2)	-0.0641	-0.3499	1	STU(t-2)	0.4492	-0.2395	1	TOY(t-2)	0.343	0.6295	1
PAC(t-3)	-0.2787	0.0791	-0.0742	STU(t-3)	0.117	0.0581	-0.2229	TOY(t-3)	0.2451	0.5396	0.7311

					AMC	AMC(t-1)	AMC(t-2)		MAZ	MAZ(t-1)	MAZ(t-2)
				AMC	1			MAZ	1		
				AMC(t-1)	0.3493	1		MAZ(t-1)	0.131	1	
				AMC(t-2)	-0.0288	0.3323	1	MAZ(t-2)	-0.148	0.098	1
				AMC(t-3)	-0.0657	0.0955	0.372	MAZ(t-3)	-0.6423	0.1097	0.22

	TOT	TOT(t-1)	TOT(t-2)		TOT	TOT(t-1)	TOT(t-2)		MIT	MIT(t-1)	MIT(t-2)
TOT	1			TOT	1			MIT	1		
TOT(t-1)	0.0516	1		TOT(t-1)	-0.0717	1		MIT(t-1)	0.3108	1	
TOT(t-2)	-0.1767	0.0396	1	TOT(t-2)	0.0611	0.3772	1	MIT(t-2)	0.1703	0.2527	1
TOT(t-3)	0.0801	-0.0086	0.0945	TOT(t-3)	0.1773	0.3659	0.8228	MIT(t-3)	-0.1241	0.1493	0.1254

Table V: Regression Results for Equation (15)

	GM pre	GM pst	Ford pre	Ford pst	Chry pre	Chry pst	Pac pre	Total pre	Total pst
units(t-1)	*-0.1218	**-0.2722	**-0.4288	***-.3035	-0.2062	**-0.8163	-0.1796	***0.2667	**-0.2098
t	-1.971	-3.253	-3.119	-3.92	-1.182	-2.652	-1.697	-4.125	-2.571
growth(t-1)	-0.0511	0.0009	0.0922	0.0734	0.1632	**-0.0025	-0.2531	0.0236	-0.0653
t	-0.279	0.0006	0.534	0.481	0.563	-0.013	-1.37	0.144	-0.493
growth(t-2)	-0.0989	-0.0486	-0.0888	-0.1002	-0.1576	0.0463	0.0799	-0.1834	-0.0236
t	-0.537	-0.359	-0.527	-0.754	-0.719	0.381	0.517	-1.197	-0.775
R	0.13	0.191	0.28	0.25	0.179	0.409	0.241	0.301	0.168
F	0.205	0.018	0.025	0.001	0.574	0	0.125	0.003	0.054
log lik	-11	19.12	-16.68	18.58	-3.604	-16.413	-8.16	-6.499	29.55
reset	0.1564	0.285	0.042	0.1949	0.1077	0.0002	0.7831	0.8252	0.3076

post-War only

	Stud	AMC	VW	Honda	Nissan	Toyota	Mazda	Mitsub
units(t-1)	0.4833	**-0.241	*-0.1588	-0.176	***-0.231	**-0.1552	**-1.45	-0.3178
t	1.544	-3.03	-1.711	-1.703	-4.194	-2.702	-3.957	-1.423
growth(t-1)	-0.674	**0.4528	0.1699	0.0027	0.0962	0.3175	**1.099	0.0784
t	*-1.853	2.168	1.118	0.014	0.487	1.189	3.192	0.303
growth(t-2)	0.1487	-0.0115	0.2836	-0.0081	-0.1613	-0.0697	**0.9275	0.1728
t	0.437	-0.053	1.826	-0.047	-0.944	-0.414	2.927	0.713
R	0.346	0.279	0.171	0.64	0.437	0.542	0.639	0.473
F	0.101	0.004	0.032	0	0.001	0	0.031	0.258
log lik	-14.98	5.51	1.32	18.41	12.28	23.1	12.58	6.08
reset	0.2643	0.2962	0.5248	0.0012	0.988	0.046	0.6546	0.7559

Note:
--***=significant at the 1% level, ** = significant at the 5% level, *= significant at the 10% level.
--Pre = pre-War, Pst = post-War.
--*Units* refer to the <u>level</u> of output (number of automobiles produced) in logs. *Growth* refers to the growth rate of output.
--The F statistic is the Prob>F.
--The Reset statistic is the Ramsey Reset test.

Table VI: Unit Root Tests

	D-F pre	D-F post
GM	**0.4661**	0.0133
Ford	0.0021	0.0027
Chrysler	**0.6196**	0
Packard	**0.4405**	
Stud		**0.9947**
AMC		**0.2641**
VW		**0.6012**
Honda		0
Toyota		0
Mazda		**0.597**
Mitsubishi		**0.3634**
TOTAL	0.0027	0.0394

We performed the D-F test both with and without a *trend* variable. The above values refer to the test with no trend. Adding a trend did not alter the results.

REFERENCES

Abernathy W.J. and K. Wayne (1974), "Limits to the Learning Curve," *Harvard Business Review, 52: 109-120.*

Abernathy, W.J., K. Clark and A. Kantrow, (1983) *Industrial Renaissance: Producing a Competitive Future for America,* XXXXX

Aoki, M. (1986), "Horizontal vs. Vertical Information Structure of the Firm," *American Economic Review,* Vol. 76: 971-83.

Cohen, W. and D. Levinthal (1989), "Innovation and Learning: The Two Faces of R&D, Implications for the Analysis of R&D Investment," *Economic Journal*, 99: 569-596.

Cohen W. and D. Levinthal (1989) "Absorptive Capacity: A New Perspective on Learning and Innovation," *Administrative Science Quarterly*, 35: 128-152.

Coriat, N. and G. Dosi (1998), "Learning How to Govern and Learning how to Solve Problems: On the Co-Evolution of Competences, Conflicts, and Organizational Routines," in The Dynamic Firm: The Role of Technology, Strategy, Organization, and Regions, Alfred D. Chandler, Jr., Peter Hagstrom and Orjan Solvell (eds), Oxford University Press, pp. 103-33.

Dosi, G. and L. Marengo, (1994) "Some Elements of an Evolutionary Theory of Organizational Competences," Evolutionary Concepts in Contemporary Economics , Richard, W. England (ed), University of Michigan Press, pp. 157-78.

Dosi, G., O. Marsili, L. Orsenigo and R. Salvatore (1995), "Learning, Market Selection and the Evolution of Industrial Structures," *Small Business Economics,* 7: 411-436.

Geroski, P. (2000) "The Growth of Firms in Theory and Practice", in N. Foss and V. Mahnke (eds) , Competence, Governance and Entrepreneurship, Oxford University Press, Oxford.

Geroski, P. and S. Machin (1993), "Innovation, Profitability and Growth over the Business Cycle," *Empirica*, 20: 35-50.

Geroski, P., and M. Mazzucato (1999), "Myopic Selection and the Learning Curve", London Business School mimeo.

Geroski, P. and M. Mazzucato (2000), "Advertising and the Evolution of Market Structure in the US Car Industry", mimeo, London Business School.

Geroski, P., I. Small and C. Walters (2000) "XXXXXXXXX"

Gibrat, R. (1931), Les Inegalites Economiques, Paris: Requeil Sirey.

Henderson, R. and K. Clark (1990), "Architectural Innovation: The reconfiguration of existing product technologies and the failure of established firms," *Administrative Science Quarterly*, 35: 9-30.

Hunker, J.A. (1983), Structural Change in the US Automobile Industry, Lexington Books, Lexington, MA.

Ijiri, Y., and H. Simon (1977), Skew Distributions and Sizes of Business Firms, Amsterdam: North Holland.

Kawahara, A. (1998), The Origin of Competitive Strength, Springer, New York.

Klepper, S. (1996), "Exit, Entry, Growth, and Innovation over the Product Life-Cycle," *American Economic Review,* 86(3): 562-583.

Malerba, F. (1992), "Learning by Firms and Incremental Technical Change," *The Economic Journal*, July 1992, p. 8545-855

March, J.G. (1991), "Exploration and Exploitation in Organizational Learning," *Organization Science*, 2: 71-87.

Nelson, R. R., and S.G. Winter (1982), An Evolutionary Theory of Economic Change, Cambridge, MA: Harvard University Press.

Pavitt, K. (1984), "Sectoral Patterns of Technological Change: Towards a Taxonomy and a Theory," *Research Policy*, 3, pp. 343-73.

Penrose, E. (1959), The Theory of the Growth of the Firm, Oxford, Basil Blackwell

Prahalad, C.K. and G. Hamel (1990), "The Core Competence of the Corporation," *Harvard Business Review,* May-June 1990, p. 79-91

Simon, H.A., and C.P. Bonini (1958), "The Size Distribution of Business Firms," *American Economic Review*, 48(4): 607-617.

Spence, M. (1981), "The Learning Curve and Competition," *Bell Journal of Economics*, 12: 49-70.

Teece, D., G. Pisano and A. Shuen (1997), "Dynamic Capabilities and Strategic Management," *Strategic Management Journal*, 18(7): 509-533.

Tushman, M. and P. Anderson (1986) "Technological Discontinuities and Organizational Environments," *Administrative Science Quarterly*, 31: 439-465

Henderson, R. and K. Clark (1990), "Architectural Innovation: The reconfiguration of existing product technologies and the failure of established firms," *Administrative Science Quarterly*, 35: 9-30.

Yelle, L.E. (1979), "The Learning Curve: Historical Review and Comprehensive Survey", Decision Sciences.

White, L. (1971), The Automobile Industry, Harvard University Press, Cambridge, MA.

NOTES

[1] For early work on the learning curve, see Asher, 1956, Boston Consulting Group, 1972, and the brief survey in Scherer and Ross, 1990, p. 98; Spence, 1981, explores the relation between learning and market structure, while Abernathy and Wayne, 1974, pursue some of the strategy implications.

[2] This is an enormous literature, one that arguably began with Penrose, 1959 and Nelson and Winter, 1982; for more recent work, see Prahalad and Hamel, 1990; Teece et al. 1997; Dosi and Marengo, 1994, Teece, 2000 and (many) others.

[3] See Cohen and Levintahal, 1989, and others.

[4] Dosi et al, 1996, pp. XXXX. For a sectoral classification of patterns of technical change, Pavitt, 1984; see also Malerba, XXXXXXXX, Dosi and Marango, 1994, and others for further work in this vein.

[5] See Tushman and Anderson, 1986, Henderson and Clark, 1990, and many others.

[6] For example, if demand is $P = \varphi_0 - \varphi_1 Q$ and costs are $C = \varphi_2 Q$, then the optimal output choice of the firm will be $Q = (\varphi_0 - \varphi_2)/2\varphi_1$. Hence, if costs are reduced or demand is increased by some sort of learning that lowers φ_2 or increases φ_0, the rate of growth of output will be positively related to the rate of learning.

[7] For early work on corporate growth rates in this tradition, see Gibrat, 1931, Ijiri and Simon, 1977, Simon and Bonini, 1958; more recent work includes .... and the overview by Sutton, XXXX.

[8] It would certainly be interesting to explore the relationship between learning and investments made to develope product or process innovations; i.e. R&D. However, we have been unable to compile an accurate series on R&D for the firms in our sample.

[9] This specification is very similar to that one often encounters in the literature which assesses the effects of patents and major innovations on corporate performance; see, for example,.....................

[10] For surveys of empirical work on spillovers, see.................................

[11] Previous work using corporate growth equations like (10) have interpreted the co-efficient λ_j as a measure of agglomeration economies; see, for example, Geroski et al, 2000. Equation (10) is also very similar to the Lotke-Volterra equation which is used by ecologists to describe the rate of growth of two populations which inhabit the same niche; see Roughgarden, 19XX, Chapter XX.

[12] This is similar to the model discussed in Geroski, 2000, which shows that a set of unobserved but durable competencies will induce a moving average in growth rates over time. In that model, one expects $\theta > 0$, reflecting the positive and persistent effects that such competencies have on corporate performance over time.

[13] The output data is the number of units produced per annum, and was obtained from annual editions of Ward's Automotive Yearbooks (published by Wards Communications in Detroit). The Innovation data was obtained from Abernathy, Clark and Kantrow, 1983, which contains a chronological list of automobile innovations by firm from 1893 to 1981.

[14] We have experimented somewhat with altering the precise dates which define the beginning and end of these periods, and it seems to make little difference quantitatively (and no difference whatsoever qualitatively) to the results which are reported in what follows.

[15] See Geroski and Mazzucato, 2000, and, more generally on the history of the industry, see Hunker, 1983; Kawahara, 1998, and White, 1971, amongst many others.

[16] There are, of course, other ways to interpret this result: see, for example, Geroski et al, 19XX, who argue that a random walk in firm size is consistent with a model in which firms hold rational expectations about the future and choose an output trajectory subject to adjustment costs.