The Impact of the Firm-Industry Life-Cycle on the Size-Wage Relationship

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Introduction

Economics has long been concerned with the heterogeneity of firm performance. Why is it that some firms perform better than their counterparts? While a rich literature emerged to account for such heterogeneity of firm performance, only more recently have scholars begun using the lens of evolutionary economics to explain variations in performance across firms. Such theories have typically linked the life cycle at both the level of the firm and the industry to account for heterogeneity with respect to firm growth, survival and profitability (Klepper, 1997). However, a different measure of firm performance has remained largely neglected in evolutionary economics – wages. The purpose of this paper is to examine how this relatively overlooked aspect of firm performance, wages, is shaped by the life cycle of both the firm as well as the industry.

In fact, there is a long tradition in economics that considers wages to be just as an important measure of firm performance as is growth, survival and profitability. As for the other performance measures, this literature has identified a systematic and compelling statistical finding linking wages to firm size. That large firms pay higher wages than small firms has become a well-established stylized fact in the economics literature. A substantial body of empirical literature seeking to explain inter firm-size wage differentials has developed since Moore (1911) first empirically documented its existence. Firm-size wage differentials lay at the heart of a larger issue, however, namely that of firm performance. While there exists an array of performance measures (employment, profits, sales, and stock prices to name a few) wages carry a particular poignant attachment to conceptual measures of welfare. One may draw a seemingly simple policy conclusion that large firms are better for their workers since all else constant, wages are higher (Brown, Hamilton, and Medoff 1990; Brown and Medoff 1989). Such a policy conclusion, however, disregards the possible insights of a dynamic analysis. Specifically, if one views industry through the more dynamic lens provided by evolutionary economics, that of a landscape that changes through time via entry, growth, stagnation, and exit, we may arrive at a different conclusion regarding the relationship between wages and firm size.

Concurrent with the development of the firm-size wage differential literature has been the recognition and importance of knowledge in the production process. While the concept of knowledge has not played a dominant role in much empirical economic research, largely because there are complex issues involved with measuring knowledge, it has played a major role in endogenous growth theory, which incorporates knowledge in static and dynamic models (Romer 1986; 1990; Lucas 1988; Krugman 1991). Using knowledge intensity as a sectoral differentiating factor has not been common (until recently) in the literature. If knowledge is an important part of growth dynamics, what role does it play in determining the survival, growth, and even wages of a firm for example? Why would one expect knowledge or "knowledge use" by a firm to play a role at all, and how does this relate to the wage differentials between large and small firms? A distinguishing feature of the industry life cycle is that new economic knowledge plays a particularly important role in the earlier stages of the life cycle but then recedes as the industry evolves towards maturity (Vernon, 1966; Wells, 1966; Audretsch, 1987). While all of these questions are not answered here, it is from this perspective that we analyze and highlight the wage performance of firms in different sectors.

In this paper we argue that there likely exists a difference in the wage growth of firms in the early life cycle stages, where knowledge plays an important role, versus industries in the more mature life cycle stages, where knowledge is less important.[1]

[1] Korobow (2002) and Audretsch and Korobow (2003) provide a more in-depth analysis of the

Specifically, will firms in the earlier stages of the industry life cycle exhibit higher wages, and perhaps higher growth in wages, since they are using an additional input in the production process, which augments the marginal productivity of labor? Further, the studies of the firm-size wage relationship, while controlling for industry effects, do not account for the presence of knowledge in a dynamic context. That is, both knowledge and non-knowledge using firms are grouped together in most cross-sectional analyses, when perhaps they should be viewed separately and in a dynamic setting when compared to large firms. Thus, the objective here is to establish or report on the firm-size wage differential in a dynamic context using the classification of the relative importance of knowledge in order to better understand the impact of the industry life cycle on the firm-size wage relationship.

In this paper we use a unique data set which links firms together to form a 14 year longitudinal data set. Specifically we analyze the change in wages associated with new and small firms in different sectors over time. Individual firm-level observations are used to analyze the change in the average wage of a cohort of firms. Essentially we ask two questions. First, does the firm-size wage differential persist when examining firm behavior under a dynamic lens rather than a static lens? And second, does the industry or sector of existence distinguish between the level of performance (wage) of new firms?

The Data

Undoubtedly, many researchers have sought to analyze the complexities of industry dynamics, but in many cases have been hindered by the lack of comprehensive data which track firms and corresponding wages over a significant time period. In fact, data sets which track new firms, employment and wages have only become more available to researchers in the past several years. [2]

Most states, through their respective Departments' of Labor, keep confidential but precise records of total wages disbursed by an establishment, as well as monthly employment. As noted by Krueger (1999), the ES-202 data entail a broad measure of wages and salary, which includes cash compensation, the realized value of stock options, and the value of any taxable fringe benefits, in addition to any employees defined as any person who is paid a salary from the establishment. For the purposes of this paper, such data are exploited. Specifically, the data set, the ES-202 Firm-Level Employment Data, contains data on monthly employment, and total wages by quarter for virtually every firm in the state of Georgia beginning with the first quarter of 1977 and ending with the fourth quarter of 1997.

The most significant drawback of the ES-202 data is the limited number of explanatory variables available. Industries of business, wages, employment, change of ownership, entry time, and exit time period are all known, however, important characteristics of workers and working conditions of the firms are not known.

Therefore, regressions, which try to determine exactly what is causing the growth or shrinkage of employment and wages over time at the firm level, for example, by using specific, more traditional independent variables, such as capital-labor ratios at the firm, information about managerial and organization structure, and technological capability relative to other firms, cannot be determined here. We do, however, control for industry characteristics in which the firms operate since we are examining the change in wages of cohorts of firms athe four-digit SIC level.

Lee and Has (1996) have produced empirical methods by which to measure knowledge. Briefly, the researchers classify industries into high and low knowledge industries based upon a number of measures including the human capital content (number of scientists and engineers, other knowledge workers, and number if employees with a post-secondary education) and R&D activity.

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wage trajectories of new and small firms in knowledge-based industries.

[2] Hamermesh (1999) emphasizes the important role of the recently available linked employer-employee (known as LEE) data in learning more about the functions of both sides of the labor market and furthering our understanding of policies. Leonard (1999) stresses that such new data will widen our perspective regarding the role of the firm in the determination of wages.

TABLE 1

SELECTED HIGH KNOWLEDGE AND LOW KNOWLEDGE INDUSTRIES

Knowledge Industries	Low Knowledge Industries
Consulting	Apparel Stores
Engineering	Mills (Textiles)
Medical/Pharmaceutical Services	Construction
Computer and Related Services	Food Stores
R&D, Biotechnology and Testing Labs	Transportation
Labs (Medical)	Home Furnishings
Communications/Telecommunications	Personnel Supply Services
	Textiles
	Woods

These measures are used to group firms into high and low-knowledge cohorts by four-digit SIC industry. This distinction between knowledge-based versus non-knowledged based industries is somewhat novel in that it presents a different perspective from the typical, traditional comparison of manufacturing versus services.

Table 1, shows the various groupings of firms by high and low-knowledge sector, while Table 2 shows a cross-sectional description of average and median wages by cohort.

Table 2 shows that the average and median wages of new firms is lower than that of all small firms and lower than firms in larger size groups. This is consistent with the established empirical literature previously discussed. However, a contrasting view is presented once industries are distinguished by knowledge intensity. New firms in knowledge industries show higher average and median wages than all new firms.

The authors note a number of more important distinctions, namely that: *i)* the average wage of new knowledge firms is higher than those of new firms in the non-knowledge industries as expected, and more interestingly, *ii)* new knowledge firms show roughly the same average or higher average wages than large firms. Though this result is cross-sectional, it shows us that by distinguishing the new and small firm by sector, a different perspective arises with regard to the traditional result of new, small firms paying lesser wages.

TABLE 2

AVERAGE AND MEDIAN WAGES OF NEW FIRMS BY SECTOR
SELECTED KNOWLEDGE AND NON-KNOWLEDGE INDUSTRIES

Sector	Average	Median
All	$6,061 (23.7)	$4,466
Small	6,059 (24.4)	4,415
Large	6,515 (115.2)	5,950
New	5,767 (74.1)	3,919
Knowledge Industries	9,768 (385.2)	6,121
Non-knowledge Industries	4,463 (66.3)	3,789

Empirical Analysis

The next step is examining the trajectory of cohorts in a dynamic context. In order to create an average wage path for a cohort of startups in a particular sector, the average wage per employee at the firm level (hereafter referred to as the average wage per firm or simply average wage) was taken for all firms in a cohort in a particular quarter. The wages over all quarters form a series, $w_t = \gamma_t + c_t$. This series possesses a trend or growth component, γ_t, and a cyclical component, c_t. We employ a simple smoothing technique in order to evaluate the actual seasonally adjusted trend in wages for a particular group of firms, and then second, employ a smoothing technique which accounts for the cyclical component of the average wage series.[3] First, to adjust for

[3] Researchers have noted that much of the employment change at the establishment level is transitory in nature or reflects short run fluctuations (Baldwin and Gorecki 1990; Davis, Haltiwanger, and Schuh 1996). Since these

the seasonal component of wages, the commonly used Census X-11 method for additive series is employed.[4]

Once the series is seasonally adjusted, a time-series filtering method is employed in order to obtain a real average wage trend for a cohort of firms which accounts for possible cyclical fluctuations.[5] Following Hodrick and Prescott (1997), the smoothed series or the true trend component of the series $\{\gamma_t\}$, is found by minimizing the variance of the actual real wage series {wt} around {γt}.[6]

The smoothed wage trajectories for four different cohorts of firms are presented in Figure 1.[7] Each cohort tracks the wage evolution of those firms, which were born in 1984. When the cohorts are placed together, as in Figures 1, the contrast between cross-sectional and dynamic comparisons of firm-wage differentials is revealing. Knowledge startups, on average, begin with higher paying wages than even large firms, as we saw in the Table 2, but the wage trajectory appears greater than the other cohorts as well, at least certainly for the first 6 years before it seems to flatten out, albeit at a higher level than all cohorts. In comparison, large firms exhibit a positive real wage trajectory as well, though the slope is of lesser magnitude.

The startup cohort begins with a lesser wage than the large firm group, and seems to close the gap over time. At first the new and small firm cohort exhibits a steeper wage slope, but it levels off and converges toward that of large firms, though as a group, new small firms never achieve the same level of wages. The poorest performing group is, as expected, the non- knowledge cohort; the group which has the lowest measures of knowledge-use in the production process. Non-knowledge firms begin at a much lower level than the other groups, while showing the overall flattest wage trajectory. In fact, the non-knowledge cohort has a wage trajectory that terminates close to where all startups as a group begin. It appears as if the firms that rely on knowledge as an input in the production process show an initial wage that is higher than the other groups as well as a greater wage slope.

Estimating Wage Trajectories

The smoothed wage series show that some groups of firms have upward sloping wage profiles while others have almost flat wage paths. The conjecture is that difference in knowledge intensities or the importance of knowledge in the production process, which is related to stage of the industry life-cycle, is related to the difference in wage paths for startups. While this non-parametric technique is useful for a graphical interpretation, it lacks the power to test an explicit hypothesis. Thus,

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employment changes are likely to influence the change in the average wage, this smoothing technique enables the researcher to avoid this measurement issue by creating what can be interpreted as the long-run trend of wages for a particular cohort of firms.

[4] The strength of the X-11 seasonal adjustment method, as opposed to using a moving average method, is that the X-11 allows the seasonal factors to change from year to year whereas with a moving average, seasonal fluctuations are assumed constant from year to year.

[5] In order to do this, the Hodrick-Prescott filter is used. This technique was developed and used by Hodrick and Prescott (1997) for representing a time series as the sum of a smoothly varying trend component as well as a cyclical component. The authors employ this smoothing method to analyze aggregate economic fluctuations or business cycles using quarterly data, thus it lends itself nicely for the analysis of real wage paths in a cohort of firms

[6] The minimization of the variance is modified by imposing a restriction which puts a constraint upon the second difference of {γt}. Thus, the explicit representation of the smoothed H-P series of wages is:

$$\underset{\{\gamma\}_{t=-1_t}^{T}}{Min}\left\{\sum_{t=1}^{T}(w_t-\gamma_t)^2+\lambda\sum_{t=1}^{T}[(\gamma_t-\gamma_{t-1})-(\gamma_{t-1}-\gamma_{t-2})]^2\right\}$$

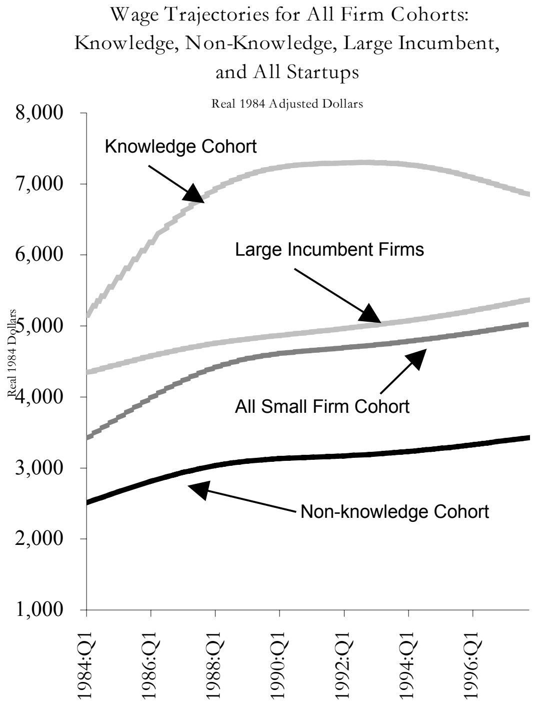
Hodrick and Prescott introduce the parameter λ, which determies the smoothness of the series by penalizing large variations in the "growth component of the series." As $\lambda\to\infty$, the smoothed series approaches an OLS, linear trend line. In the data analysis here, the smoothing parameter λ is specified to be 1600, standard for quarterly data. As observed from a sample of data, the wage paths generated by the average wage per employee for each firm are smoothed functions that have been controlled for cyclical and seasonal fluctuations.

[7] The smoothed wage trajectories for the sub-sectors of each overall grouping are available upon request from the authors.

in this section a simple wage slope is estimated using OLS. This wage slope is then used in order to test two hypotheses of interest::

i) do wage trajectories differ statistically between large firms and new firms?; and

Figure 1.



ii) do wage trajectories differ for new firms in the two different sectors?

In order to get a conditional estimate of the wage trajectory, $\dot{w}$, a trend equation, as in 5-1, is estimated for each cohort of firms. This model estimates the conditional wage trajectory since only surviving firms are observed. In 5-1, w_{ij}^t, is the wage paid by a firm in the i^{th} group, in the j[th] sector, knowledge or non-knowledge; β_0, is an intercept, which can be interpreted as the initial average wage for a cohort of firms; T, is an index variable which measures time in quarters; β_{ij} is the slope coefficient estimate for a cohort of firms in a specific sector; β_δ is the dummy coefficient for controlling for seasonal fluctuations.

$$w_{ij}^t = \beta_0 + T\beta_{ij} + \beta_\delta \delta + \varepsilon_{ij}^t \qquad (1)$$

From 5-1, β_{ij} becomes the estimate of $\dot{w}$, since $\frac{\partial w_{ij}^t}{\partial T} = \dot{w} = \beta_{ij}$.[8] This model for wage trajectories is estimated for large firms, all new firms, all knowledge firms, all non-knowledge firms, and for each subset of firms listed in Table 3. The wages are in real 1984 dollars,

[8] Other researchers have noted the selection issues involved in studying changes in cohort-level and firm-level variables over time (Evans 1987a, 1987b; Hall 1987). In particular, the measurement of these variables, for example, growth, is influenced by exiting firms, thus giving rise to a censored sample, and subsequently raising the issue of selection bias. In some cases, researchers "force" a balanced panel in which only firms that survive through the period of analysis are used. This presents the problem of survivorship bias in the results. The proper control in most cases would be to estimate a probit model on firm survival to obtain the probability of whether or not firms enter the sample, following Evans (1987a). The results are used to create a variable, which captures this probability of entering the sample to develop the inverse of Mill's ratio detailed by Heckman (1979). Subsequently, this variable is entered into the least squares regression. The sample inclusion equation, as noted by Evans (1987, 573), "is ad-hoc and has no economic interpretation."

In light of the previous research that has sought to isolate the effects of self-selection, a control for attrition bias is included in the analysis that attempts to explain the difference in wage trajectories across three-digit industries. However, where the wage trajectories for the individual knowledge and non-knowledge cohorts are estimated, no controls for selection bias are included. As noted by Heckman's (1979) seminal research on selection, if the probability of being included in the sample is the same for all observations then the conditional mean of the error term in the wage equation, ε_{ij}^t, is a constant, and the bias which arises from using the selected sample of firms only occurs in the estimate of the intercept. Since only the slope coefficient is used for the analysis here, and the intercept is not used for any purpose in this research, there is no control made for sample selection.

TABLE 3
ALL FIRMS

WAGE SLOPE ESTIMATES ($\dot{w}$)
(1984 Dollars)

Sector/Cohort	7-Year Wage Trajectory	12-Year Wage Trajectory
Large	$16.3**	$12.8**
	(1.7)	(1.0)
All New	36.7**	26.8**
	(1.3)	(0.8)
Knowledge	86.1**	54.9**
	(6.4)	(3.9)
Consulting	45.1**	25.2**
	(9.2)	(5.3)
Engineering	52.2**	26.3**
	(8.5)	(4.7)
Medical Services	142.5**	83.3**
	(13.8)	(7.8)
Computer and Related Services	77.2**	42.6**
	(13.0)	(7.6)
R&D, Biotechnology and Testing Labs	68.5**	60.2**
	(17.3)	(10.8)
Labs (Medical)	48.0**	11.1*
	(10.3)	(5.6)
Communications/Telecom-munications	86.9**	14.4
	(22.8)	(13.3)
Non-knowledge	20.6**	15.2**
	(1.3)	(0.8)
Apparel Stores	3.7*	5.0**
	(1.8)	(1.1)
Mills (Textiles)	-2.6	5.2
	(10.9)	(5.9)
Construction	20.7**	15.1**
	(1.8)	(1.1)
Food Stores	8.5**	3.6**
	(1.4)	(0.8)
Transportation	7.5*	9.0**
	(3.4)	(1.8)
Home Furnishings/ Furniture	23.3**	10.0**
	(3.4)	(1.9)
Personnel Supply Services	10.6**	6.8**
	(1.9)	(1.0)
Textiles	47.2**	11.8*
	(9.1)	(4.9)
Woods	23.3**	24.4**
	(2.8)	(1.7)

Standard errors in parentheses
**Significant at the .95 Level of Confidence for a two-tailed test*
***Significant at the .99 Level of Confidence for a two-tailed test*

and thus the slope represents a real wage trajectory estimate.

Table 3 shows two different estimates for the wage slopes in each cohort. The first and second columns show the respective OLS estimated wage trajectories for the first seven and twelve years of the cohort's existence.[9] Each estimate should be interpreted as the average change of the real wage for each quarter. For example, large incumbent firms show an increase of about 16.30 real 1984 dollars per quarter, when using the first seven years of the data.

Table 3 brings to light some new and interesting empirical insights. The slope estimates for each cohort are significant at conventional levels, except for the *Textile Mills* cohort, at both the seven- and twelve-year time horizons, and the C*ommunications/ Telecommunications* cohort at the twelve-year horizon. First, one immediately notices that, in most cases, the wage growth for the seven year sample is greater than that of the twelve year sample, suggesting that most new firms, given survival, experience most of the growth in wages over the first several years of their existence. In fact, this pattern of higher wage growth in the early years of a firm cohort is suggested by the smoothed wage paths exhibited in the previous section. Thus it appears, that wages for all cohorts except for large firms exhibit higher wage growth over the first seven years. When the analysis focuses on the twelve-year estimates, there is a significant "flattening" of the wage slope.

Table 3 may be piecing together two snap- wages shots from separate points in time—the changes in wages of large established firms versus those of the new firm. This empirical finding, viewed together with the empirical result that the average size (measured by employment level) of cohorts grows over time, would, in fact, suggest that larger firms should show lower growth rates in, assuming that their firm capital has proportionately slower growth rates as well. More specifically, it is likely that, given survival and an increase in firm size, the growth rate of the wages would decrease though time, as the firm grows larger. In

[9] There is no particular theoretical motivation for examining the wage trajectories over seven years of data. However, this time period is used following Mata et al. (1995) who analyze the behavior of plant births over a seven-year period. This time period may also have some significance as suggested by Audretsch (1995b) and Boeri and Cramer (1992) who find that plants roughly double in size six years after entry.

other words, the large incumbent firms show the lowest growth rates because they are in a later evolutionary stage than the new firms.

The results in Table 3 further reinforce the non-parametric results from the previous section that depicted a non-linear path of wages. When compared, the seven- and twelve-year estimates of wage slopes show that the wage growth rates in firms are perhaps non-linear in nature with respect to age. That is, the wage slopes of surviving new firms appear to be concave in time, since in most cases the seven-year slope is greater than the twelve-year slope.

The next interesting result in Table 3 arises from the sectoral distinction. The wage trajectory for all large incumbent firms appears to be smaller than that of all new firms over both the seven and twelve year periods. Additionally, the large-firm cohort appears to have a lower trajectory than that of each knowledge cohort and all knowledge cohorts estimated as a group for the seven-year period. The same result holds as well for the twelve-year wage slopes except for the *Medical Labs* cohort, which shows a slightly lower trajectory than large firms.

The wage trajectories of non-knowledge firms stand in stark contrast to the knowledge cohorts and all new firms. For all knowledge firms, the average wage changes about \$86 per quarter—greater than all new firms' change of \$36.7, and greater than all non-knowledge firms' change of \$20.6 for the seven-year period. For the twelve-year period, the wage increases, or average wage change is not as pronounced, but clearly the knowledge cohort still shows a greater wage slope than the other groups. Moreover, the non-knowledge cohorts show the flattest wage slopes. The *Textile* cohort, which over the first seven years shows an almost anomalous trajectory when compared to other non-knowledge firms of about \$47, flattens out to about \$11 over the twelve year period. This would suggest that at first the cohort experiences rapid wage growth, but when analyzed over a longer period the wage trajectory levels off rapidly.

The most important contribution represented by Table 3 is twofold. First, it shows clearly that while many new firms pay lower wages than large firms, their tendency is to show greater growth in wages over time as measured by their respective wage slopes. This indeed sheds light on the firm size wage differential in that, while large firms pay higher wages, some small firms may actually catch up to their larger counterparts though time.

Second, it is apparently important to distinguish between the sector of origin when examining new firms. That is, there is a difference between the knowledge startup and the non-knowledge startup in that their respective wage paths appear to be markedly divergent. Thus, when analyzing the new firm and the expected wage or the possible wage paid by that firm, it appears that startups in the knowledge industries enjoy greater wage growth, especially in the first seven years.

Knowledge Indicators and the Wage Trajectories of New Firms

In this section we use knowledge measures similar to those employed by Lee and Has (1996), in order to examine the role of knowledge intensity in determining the difference in wage trajectories of new and small firms across sectors. Rather than using two-digit industry data, which may not allow for sufficient variation across sectors, three-digit SIC industry level data are used. Data are used for the years 1984-1991, since each year provides a separate cohort of startups for each industry. Other data sets are used to gather information at the industry level, thus compensating for the lack of characteristics at the firm level in the ES-202 data.

The Current Population Survey (1990) is employed in order to gain general industry characteristics at the three-digit level. Though the CPS does not report three digit industry level characteristics, it does classify observations based on an occupational code used by the Bureau of Labor Statistics. This occupational code has a conversion for three-digit industry level. Subsequently, these conversions were used to gather information about the general characteristics of workers in a particular industry. These data were then merged with the ES-202 data to yield a new data set, which has wage trajectories and industry level information about the workers in that industry.[10] All of the variables relevant for the regression analysis and their respective values associated with the industries are presented in Appendix Table 17.

If one considers the knowledge production function originally introduced by Grilches (1979), the critical input is new economic knowledge. For this reason, the best measures of new economic knowledge or knowledge production used here will be the innovative intensity and relative R&D intensity in an industry. Previous research has asserted that R&D may be the best measure of new economic knowledge (Cohen and Klepper 1991). The interpretation of innovation or invention as production of knowledge is consistent with many other researchers, namely Arrow (1962) who notes in the very first sentence of his classic article, "Economic Welfare and the Allocation of Resources for Invention": "Invention is here interpreted as the production of new knowledge" (609). Audretsch and Feldman (1996a) point out that "the greatest source that generates new economic knowledge is generally considered to be R&D" (258-259). Rather than use the rankings of R&D intensity and innovation measures reported by Lee and Has, (since the data are for Canada they may not be conformable with the United States) data are gathered from a unique innovation data base released by the US Small Business Administration in the latter half of the 1980's, as well as the National Science Foundation's data base on R&D statistics.

In order to gather innovation data which can be used to measure the prevailing technological regime in an industry where the introduction of new ideas or the advent of new knowledge is important to the survival of firms, a database reporting innovations by 4-digit SIC industries, first exploited in research conducted by Acs and Audretsch (1990), is used.[11] These innovations data, released by the US Small Business Administration, report the number of innovations recorded in the year of 1982.[12] From these data, the number of innovations for small firms can be calculated at the three-digit industry level. Here, the definition of innovation will be the same as that employed by the Small Business Administration which, as reported by Acs and Audretsch (1990, 10-11), is defined as, "a process that begins with an invention, proceeds with the development of the invention, and results in introduction of a new product, process or service to the marketplace (Edwards and Gordon 1984, 1)." For the purposes of this research then, an innovation is interpreted as new knowledge or as knowledge creation.

Dividing the number of innovations reported in a particular three-digit industry by the number of employees in that industry creates the innovation rate. This method of computing the innovation rate follows Audretsch (1995a).[13] Since the number of employees in an industry at the three digit SIC level is not readily available, the 1986 edition of the Census Bureau's *County Business Patterns* which has employment at the four-digit SIC level was used to create the three digit level employment data.

The data reported by the NSF span the time period from 1987-1997 and reflect the total funds (company, federal and other) for industrial R&D performance by industry. Averaging the individual industry percentage of total R&D expenditures in a given year across all years available creates the variable *R&D*. In many cases, R&D data are not reported for all of the years in the time period so that the confidentiality of certain companies' R&D expenditures is preserved. Consequently, the average of the expenditure

[10] Of course the significant assumption here is that average characteristics of a 3-digit industry in Georgia are not dissimilar to that of the United States as a whole. This assumption is not unrealistic unless one maintains that the economic processes of industry evolution are different in Georgia than the rest if the United States.

[11] Audretsch (1991) has shown that the small firm innovation rate is positively related to the likelihood of survival.

[12] For a full and complete description of the *Innovations Database*, please see Acs and Audretsch (1990).

[13] This innovation rate is analogous to the rate produced by Audretsch (1995a) except that he divides the number of innovations in a four-digit industry by the number of employees in firms with under 500 workers.

percentages for the years for which data do exist is used.

Another variable created using the NSF data is the number of full-time-equivalent R&D scientists and engineers in R&D-performing companies. Here, the three-digit employment data is once again used by dividing the number of scientists by the number of employees in an industry to create a variable that measures R&D scientist intensity. This variable is converted to represent the number of scientists per 1,000 workers. In the cases where data were reported at the two-digit SIC level, the percentage of R&D expenditures in that 2-digit industry was divided by the number of three-digit industry levels associated with that particular two-digit industry. This was done in order to derive the measure for that particular three-digit industry. Though this measure is not perfect, the implicit assumption is that the R&D-scientist intensity percentage is roughly the same across those three digit industries.

The regression analysis proceeds by estimating three models where the wage trajectory is calculated for each three-digit industry and used as the dependent variable in a separate regression. Recall equation (1), which is designed to estimate a linear wage trajectory. This model is estimated here for three-digit industries. The slope coefficient obtained from the estimation is used as the dependent variable in the regression models below.[14] Table 4 gives a brief description of each explanatory variable used in the models

These regression models are novel in that, we do not know of previous studies which use a dynamic measure of wage change associated with a new firm as a dependent variable while regressing this measure on indicators of industry specific knowledge intensity.[15] For this reason, a number of different specifications are examined in order to ensure the robustness of the relationships between the knowledge indicators and the trajectory of wage slopes of new firms. Models (1) through (3), use the first seven years and the first 12-years of a cohort's existence as the basis for a separate set of regression estimates to estimate the wage slopes which are then used as the dependent variable in different regressions. The seven-year wage trajectories are measured for all cohorts of startups—those from 1984 through 1990, while the 13-year estimates are for the years 1984-1996.

TABLE 4
DESCRIPTION OF EXPLANATORY VARIABLES*
MODELS (1)-(3)

VARIABLE	DESCRIPTION
RD	Average Percent of total industry R&D expenditures (company, federal and other) over the period 1987-1997, as reported by the *NSF*
SFINOVRATE	*The Small-Firm Innovation Rate* is created by dividing the number of innovations made by *small* firms in a particular three-digit industry by the number of workers in that same industry, and then multiplying by 1,000 to get the number of innovations made by small firms per 1,000 workers
LFINOVRATE	*The Large-Firm Innovation Rate* is created by dividing the number of innovations made by *large* firms in a particular three-digit industry by the number of workers in that same industry, and then multiplying by 1,000 to get the number of innovations made by large firms per 1,000 workers
SCIENT	A measure of the *scientist intensity* of an industry. Created by dividing the average total number of full-time equivalent R&D scientists and engineers in R&D performing companies as reported by

dependent variable represents a dynamic measure of wages associated with a specific cohort of firms.

[14] The respective estimates for the wage trajectories of the different three-digit industries are available from the authors upon request

[15] These models are slightly similar to those employed by Bayard and Troske (1999) in that there are some labor market variables included. However those authors analyze the level of wages across firms and industries, and do not include measures of industry knowledge intensity. Here, we focus on indicators of knowledge as explanatory variables and the

	the NSF over the period 1987-1998, by the total employment of that particular industry, multiplied by 1,000
GRAD	Percentage of workers in an industry obtaining some level of graduate school education
COLLEG	Percentage of workers in an industry obtaining some level of college education
AGE	The average age of the workforce in a particular industry
HRSWORK	The average number of hours worked in a particular industry
UNION	The percentage of workers in an industry reporting association with a union.
FAIL	The seven-year failure rate for new firms in a particular industry
GEOG	The percentage of all new firms in an industry residing within an MSA.
COHORT	A dummy variable for each group of new firms in a particular industry. (Note results on dummy variable coefficients are interpreted as the difference from the 1984 cohort.)

The first model to be estimated employs some of the measures of knowledge previously described, and adds the average level of schooling associated with a particular industry—from zero years of education to schooling at the graduate level. Bates (1990) has emphasized the importance of the educational attainment of a proprietor in determining the survival and growth capacity of the firm. Model (1) is *basic* in that it employs most of the measures of knowledge used by Lee and Has (1996).

The second model makes a finer distinction regarding the level of education. Specifically, it divides education into two separate variables—one for the percentage of persons in an industry who have a college level education and the other for the percentage of persons with a graduate level education.

The third model adds more labor market variables. Specifically, the average level of worker experience in an industry is added. The age variable attempts to control for the level of experience across industries. Though the relationship between age of a workforce and growth of a new firm may be unclear, one may conjecture the possible different relationships between age of the workforce or proprietor and firm growth. Perhaps industries with more experienced workers show higher wage paths of new firms than those which have less experienced workers. In such a scenario, experience is necessary for growth and survival in an industry.

Model 1:

$$\dot{w}_i = \beta_0 + \beta_1 RD_i + \beta_2 SFINOVRATE_i + \beta_3 LFINOVRATE_i + \beta_4 SCIENT_i + \beta_5 EDUCA_i + \beta_6 FAIL_i + \beta_7 COHORT_i + \varepsilon_i$$

Model 2:

$$\dot{w}_i = \beta_0 + \beta_1 RD_i + \beta_2 SFINOVRATE_i + \beta_3 LFINOVRATE_i + \beta_4 SCIENT_i + \beta_5 GRAD_i + \beta_6 COLLEGE_i + \beta_7 FAIL_i + \beta_8 COHORT_i + \varepsilon_i$$

Model 3:

$$\dot{w}_i = \beta_0 + \beta_1 RD_i + \beta_2 SFINOVRATE_i + \beta_3 LFINOVRATE_i + \beta_4 SCIENT_i + \beta_5 GRAD_i + \beta_6 COLLEGE_i + \beta_7 AGE_i + \beta_8 HRSWORK_i + \beta_9 UNION_i + \beta_{10} FAIL_i + \beta_{11} GEOG_i + \beta_{12} COHORT_i + \varepsilon_i$$

On the other hand, maybe young entrepreneurial firms are associated with younger workers with less experience but who are anxious to take advantage of new knowledge that they do not perceive can be executed with larger firms. Indeed, Cortes et al. (1987, 165) have asserted that the age of the entrepreneurs may be an important determinant of the growth of new firms. Specifically, they argue that while older proprietors have more experience, they may hinder the growth or be "less inclined or less able to make their firms grow." Evans and Leighton (1989), however, have suggested that there is no tendency for certain aged workers to migrate to specific firms, large or small.

The hours-worked variable attempts to control for the variance in worker hours across industries, although, as it turns out, this variable is never significant. The union variable is also added to capture the presence of industries where unionization may play a role in wage determination and wage growth. However, this researcher does not expect this variable to be significant here, since the union-wage effect is mostly associated with larger firms, and rarely with new and small firms and micro-enterprises. While this variable has been found in many studies to be positively associated with wages, it is not clear if there will be a relationship to a dynamic measure of wages associated with new and small firms.

In order to control for the possible selection bias (discussed earlier) in estimates of the different wage trajectories across industries, the seven-year failure rate of firms in a given industry is added to the model as well. Since the focus is now on explaining the variation of wage trajectories across industries, the failure rate is included to control for the possibility that lower wage paths in certain industries are associated with a higher probability of failure. That is, the failure rate may be related to the less efficient and ultimately unsuccessful firms that pay lower wages. The empirical goal is to thus control for a possible negative relationship between industries with higher failure rates and the change in wages paid by new firms through time. The idea is that lower wage-paying firms, or the firms that do not show an increase in wage through time, may be more closely associated with failing firms than higher wage-paying firms or firms that show an increase through time. This point, in fact, is somewhat touched upon by Troske (1996), who finds that failing firms show the largest drop in growth a year before exiting and suggests that this may be because firms which are nearing exit or are in the midst of the failing process attempt one last effort to succeed by laying off workers in an effort to cut costs. This reasoning would also suggest that such firms induce pay cuts or institute a no-wage-increase policy in an attempt to keep costs low as well. Further to this, one would then expect a positive relationship between wage trajectories and survival, since firms may keep wages low in the beginning in order to find ways to be efficient and survive long enough to grow. If growth does occur, then wages may rise through time. This point is developed and discussed by Audrestch, Van Leeuwen, Menkveld, and Thurik (2001).

The last variable incorporated in model (3) captures the percentage of the industry start-ups that are located in urban areas. This is important, particularly in light of a well-developed and growing body of literature that suggests that innovative activity tends to spatially cluster, and that "tacit knowledge" may be a large factor in determining innovative activity (Audretsch and Feldman 1996a, 1996b). If particular geographic locations are associated with innovative behavior or knowledge creation then this must be included in the regression analysis. Moreover, the urbanization variable has another important characteristic in that all the urban areas in the analysis have some form of higher education whether it is many universities, like in Atlanta, or smaller state schools, as in Macon. Research has emphasized that knowledge created and perpetuated by universities spills over to the private sector in the form of innovations by firms (Jaffe 1989; Acs, Audretsch, and Feldman 1994, 1996). Audretsch (1998) has emphasized the role of geography in innovative activity and the role of "spatially restricted" knowledge spillovers. Other researchers have found that the location of firms is critical in their growth. Specifically, McPherson (1996) finds that "agglomeration externalities imply that urban-based firms will grow faster than those located in rural areas" (260). In addition, McPherson suggests, "that firms grouped together in urban areas may be able to specialize in particular products and produce at lower cost than would otherwise be the case" (259). Other research has emphasized the role of agglomeration externalities in firm growth as well (Piore and Sabel 1984; Sengenberger et al. 1991; and Pyke et al. 1990).

All three models are estimated a second time using the maximum time length of data. That is, a wage slope is estimated for each cohort of firms in each three-digit industry for the years 1984 through 1990. Thus, the 1984 cohorts use 14 years of data, 1984 to 1997, while the 1985 cohorts only use 13 years of data, and so on. Though the cohort dummies were dropped from the first set of regressions which use only seven years of data for each cohort, the estimation of models (1) though (3) shown in Table 6 employ cohort dummies since the different lengths of data may affect the magnitude of the slope. In fact, the possibility of the non-linearity or the time-dependency of the slopes is implied earlier in this paper where it is depicted that cohorts of new firms—especially in the knowledge-sector—seem to experience a rapid rise in wages in the first several years and then a leveling off. Thus, it is necessary to control for this possible difference in wage slope magnitudes by adding the cohort dummy.

Empirical Results

Table 5 shows the results of the three model specifications using the seven-year wage trajectory estimate for each cohort of firms from each year. Table 6 shows the results of the model estimates, which include the maximum time-length of data available for each cohort, and a dummy variable for each cohort based upon the year of entry.

In general, the regression results support the hypothesis that knowledge, or the presence of knowledge in the production process, is an important and statistically positive influence on the wage trajectories of new firms. Apparently, the lower the knowledge content of an industry, the lower the wage trajectories of new firms. Before examining the results of the model estimations more closely, however, this researcher emphasizes that the coefficients should be carefully interpreted. Since some measures of the explanatory variables used for different industries are numerically equivalent, so that there are repeating values across some industries, and industry-level data have been matched with cohort-level information, one should cautiously interpret the exact magnitude of the coefficients. In other words, if we take the coefficient on the small firm innovation rate, *SFINOVRATE*, in model (1) of Table 5, for example, one should emphasize the positive relationship between the small firm innovation rate and the wage trajectories of new firms as the primary research contribution, rather than exact magnitude of this relationship.

TABLE 5
ESTIMATES OF THE EFFECT OF KNOWLEDGE INDICATORS ON THE WAGE TRAJECTORIES OF NEW FIRMS
THREE-DIGIT INDUSTRIES-SEVEN YEAR WAGE PATHS

VARIABLE	MODEL 1	MODEL 2	MODEL 3
Intercept	-80.15** (2.31)	17.07 (1.12)	-49.90 (1.60)
R&D	10.93** (1.97)	10.67** (1.97)	10.65* (1.97)
Small Firm Innovation Rate	289.55*** (2.59)	225.42** (2.06)	205.71* (1.87)
Large Firm Innovation Rate	-201.83 (1.47)	-130.29 (0.97)	-144.59 (1.08)
Scientist Intensity	-0.57* (1.91)	-0.73** (2.51)	-0.72** (2.45)
Education	10.83*** (4.77)	-	-
Failure Rate (Selection Variable)	-41.21* (1.74)	-33.49 (1.44)	-29.36 (1.24)
Graduate Degree	-	245.70*** (5.03)	202.17*** (4.00)
College Degree	-	39.14** (2.46)	32.32* (1.76)
Experience-Age	-	-	1.94** (2.35)
Urban Location	-	-	38.54** (2.01)
Hours Worked	-	-	-0.35 (0.64)
Unionization	-	-	-25.90 (0.91)
R^2	0.12	0.17	0.21
Adj- R^2	0.10	0.15	0.18
F-Value	6.67***	8.36***	6.94***
Sample Size	301	301	301

Standard errors in parentheses
**Significant at the .90 Level of Confidence for a two-tailed test*
*** Significant at the .95 Level of Confidence for a two-tailed test*
****Significant at the .99 Level of Confidence for a two-tailed test*

The positive and statistically significant coefficient for R&D in all of the model specifications implies that industries with a higher percentage of total R&D

expenditures are associated with new firms that yield greater wage trajectories. The magnitude of the coefficient does not change much across the regression models adding robustness to this result. However, the results do suggest that this measure of knowledge is significantly, in a statistical sense, associated with startup firms that impart steeper wage slopes.

The next measure, or indicator of knowledge, is the small firm innovation rate. As the t-statistics across all model specifications indicate, the coefficient is positive and statistically significant even using the different wage slope measures (derived from the seven year or twelve year period of data) as the dependent variable. This coefficient suggests that in industries with a higher innovation rate among small firms, the greater the wage path of the new firms in those industries relative to less innovative sectors. This is consistent with the hypothesis that knowledge conditions or the prevailing technological regime plays a role not only in the survival of firms as shown by Audretsch (1991,1995a) and Acs and Audretsch (1990), but also in the trajectory of wage compensation of these new businesses. Though these wage paths are an alternative to a less traditional method of measuring firm performance, one might still conclude that the innovative behavior of new firms is associated with higher growth.

The results for another of the industry level knowledge indicators used, the R&D scientist intensity measure, are unanticipated. The coefficient on this variable is negative and significant and suggests that new firms in industries with more full-time employed R&D scientists per 1000 workers experience lower wage growth than those with fewer scientists. Why might this be? First, perhaps some of the explanation lies within the make-up of industries that employ research and development scientists. This variable does not incorporate, for instance, a scientist that launches a new firm on her own, but likely measures the scientist employed by a big firm in its R&D department. For example, over the period 1987-1998, 46.4 percent of the fulltime employed R&D scientists and engineers were working in firms with over 25,000 workers. Moreover, 82.5 percent of these workers were employed by firms with over 500 workers, thereby leaving under 18

TABLE 6
ESTIMATES OF THE EFFECT OF KNOWLEDGE INDICATORS ON THE WAGE TRAJECTORIES OF NEW FIRMS
THREE-DIGIT INDUSTRIES
WAGE PATHS ESTIMATED FOR THE MAXIMUM TIME-LENGTH OF DATA FOR EACH COHORT

VARIABLE	MODEL 1	MODEL 2	MODEL 3
Intercept	75.48***	1.85	-63.71***
	(2.90)	(0.15)	(2.77)
R&D	11.49***	11.22***	10.59***
	(2.80)	(2.81)	(2.66)
Small Firm Innovation Rate	234.32***	180.61**	176.98**
	(2.83)	(2.24)	(2.19)
Large Firm Innovation Rate	-92.73	-30.25	-33.03
	(0.91)	(0.31)	(0.34)
Scientist Intensity	-0.62***	-0.74***	-0.70***
	(2.81)	(3.44)	(3.24)
Education	8.21***	-	-
	(4.82)		
Failure Rate (Selection Variable)	-6.52	0.06	-2.70
	(0.37)	(0.00)	(0.15)
Graduate Degree	-	178.08***	141.29***
		(4.96)	(3.82)
College Degree	-	39.79***	33.85**
		(3.40)	(2.51)
Experience-Age	-	-	1.44**
			(2.38)
Urban Location	-	-	23.30*
			(1.65)
Hours Worked	-	-	0.32
			(0.81)
Unionization	-	-	-27.31
			(1.31)
Cohort 1985	-2.11	-2.36	-1.88
	(0.30)	(0.35)	(0.28)
Cohort 1986	-6.93	-7.07	-6.36
	(0.98)	(1.02)	(0.94)
Cohort 1987	-11.45	-11.75*	-11.03*
	(1.64)	(1.73)	(1.66)
Cohort 1988	-8.19	-8.21	-7.38
	(1.18)	(1.22)	(1.12)
Cohort 1989	-7.54	-7.51	-7.11
	(1.09)	(1.12)	(1.08)
Cohort 1990	9.35	9.51	10.28
	(1.34)	(1.41)	(1.55)
R^2	0.18	0.23	0.27
Adj- R^2	0.14	0.19	0.23
F-Value	5.22***	6.50***	6.21***
Sample Size	301	301	301

Standard errors in parentheses
**Significant at the .90 Level of Confidence for a two-tailed test*
*** Significant at the .95 Level of Confidence for a two-tailed test*
****Significant at the .99 Level of Confidence for a two-tailed test*

may be the high degree of collinearity among the *RD*, *EDUCA*, and *SCIEN* variables.[16] When measures of R&D

[16] This possibility was examined by re-estimating models (1) and (3) and omitting the *RD* variable and measures of education. The

percent to work at firms with less than 500 workers.[17] This variable also measures the workers who perform research at R&D performing companies. Most small and new firms do not have R&D departments or do not officially report R&D, largely because of their size and because they are more likely to allude surveys. Thus, this measure may be more indicative of industries where large firms conduct most of the R&D and small firms do not promote their own viability by engaging in R&D but rather increase chances of survival by innovating.

Interestingly, the coefficient on the large firm innovation rate, though not significant at conventional levels, is negative. This, along with the negative coefficient on R&D scientists, would perhaps suggest that industries characterized by large-scale, established R&D operations are not conducive to the growth in wages of new firms because they present unfavorable environments for the growth and survival of new firms in the first place.

A second and more "statistically tangible" explanation for the negative sign on the scientist intensity coefficient

and education are omitted, the sign on the scientist intensity coefficient switches and becomes positive in all models, save for "version two" of model (3). In all cases, however, the coefficient is statistically insignificant.

A third possibility for the unanticipated sign on the *SCIEN* coefficient may simply be that this variable is a poor measure of scientist intensity, and does not capture enough variation from one industry to the next to function as a reliable indicator of knowledge which can add explanatory power to the models.

All of the measures of human capital are highly significant and positive as expected. Education, as measured in the years of schooling, is significant in both versions of model (1)—using both the seven and twelve years of data. When education is broken down into the average level of workers with a graduate and college degree, both measures are significant in models (2) and (3). This, of course, suggests that, as expected, the human capital content of an industry is positively related to the growth in wages in of new firms in that industry. Experience, as measured by age, is significant and positively related to the wage paths of new firms as well. Experience in this case may represent industries whose workers have learned more or have more knowledge. This would not seem to support the assertions of Cortes et al. (1987) mentioned earlier.

Geographic location is also related to the path of wages. Specifically, the proximity to an urban center is significant in model (3) in both regressions. This suggests that startups located in urban regions exhibit higher growth in wages. This adds to the previously mentioned literature on firm growth and survival in the context of geographical location. Not only do firms in geographic centers grow faster, as reported by McPherson (1996), but the result here suggests that their wages may grow faster as well. The geography and human capital variables are related in that urban centers are usually characterized by higher human capital content of workers. Thus, it seems reasonable that there is some interaction between these two variables.

The hours worked variable exhibits an insignificant coefficient. This variable was added as a control for industries where workers might work greater than the average number of hours. However, in both versions of model (3), this coefficient is not significant, and in one case, in Table 13, the sign is actually negative.

The coefficient on the failure rate variable is insignificant in all models except for model (1) estimated using only seven years of data. In all cases except for the second estimation of model (2), the sign on this coefficient is negative as expected, suggesting that industries with higher failure rates are related to lower growth rates or lower trajectories of wages in new firms. Failure seems to be inversely related to wage growth of new and small firms. In addition, industries with higher failure rates may be representative of an environment that is not

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results for these estimations are available from the authors upon request.

[17] Source: *National Science Foundation*; Table A-52. Number of full-time-equivalent (FTE) R&D scientists and engineers in R&D-performing companies, by industry and size of company: 1987-98.

conducive to the survival and growth of small firms. Thus, if firms enter, and as Audrestch et. al. (2001) maintain, keep their wages low as a competitive strategy in order to promote survival, but never actually succeed, then their wages would wither, stagnate, or shrink. Thus, a higher failure rate may signify an industry in which the knowledge conditions are such that the industry is less prone to entry. Nonetheless, since this coefficient is insignificant, the presence of selection bias is rejected as in many of the other studies on firm growth and, therefore, this researcher hesitates to make further inference in relation to this variable.

Conclusions

This paper has explicitly explored the differences in wage paths of new firms and large firms in an evolutionary setting. In particular, it has linked the performance of firms, measured in terms of wages, to both the firm and industry life cycles.

First, the wage trajectories of all new firms, large firms, new-knowledge sector firms, and new non-knowledge sector firms were estimated. A comparison of the resulting estimates showed that non-knowledge and large firms have wage trajectories of the least magnitude. Knowledge firms have wage slopes of the greatest magnitude relative to the other groups, and all new firms showed greater wage slopes than large firms and non-knowledge firms. Thus, the evidence presented in this paper suggests that in a dynamic setting the firm-size wage differential between small and large firms shrinks, and shrinks faster for knowledge startups, while the gap between non-knowledge startups and large firms may close more slowly if it closes at all.

A statistical comparison of new firms showed that the wage slopes of knowledge startups exceed those of non-knowledge startups for most of the cohorts compared. In order to explicitly examine if the knowledge intensity of an industry is related to the wage profiles of startups, indicators of knowledge were used as explanatory variables in three separate model specifications to explain the difference in these wage trajectories. These three model specifications were estimated separately using both seven and twelve years of data. The results of the estimation support the hypothesis that new firms in knowledge intensive industries exhibit wage trajectories of greater magnitude than those in non-knowledge industries.

Thus, the presence of knowledge or its use in the production process is shown to be positively related to another measure of firm growth—the wage. Thus, this research presents an alternate perspective to understanding what determines economic performance. While the cross-sectional, static perspective in the previous literature has provided numerous insights into the determinants of economic performance, this dissertation has suggested that additional, and not always compatible, insights can also be ascertained from a dynamic perspective. This dynamic framework implies that economic agents—individuals as well as firms—are engaged in a constant process of change and evolution. It may be that the lens provided by such an evolutionary framework proves to be more fruitful in yielding insights as to what actually generates economic performance. Certainly in the case of new and small firms, what appears to be a less desirable performance when viewed through the lens of a static framework becomes considerably more desirable when viewed through the lens of an evolutionary framework.

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