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Speed of Entrepreneurial Learning and Firm Growth

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Abstract

Building on the model developed by Parker (2006), I inquire whether a higher entrepreneurial speed of learning is desirable, and whether there is a linkage between the speed of learning, which is specific to the entrepreneur and the rate of growth shown by the firm? Using the Kauffman Firm Survey, changes in the speed of learning are measured for the initial six years of the firm's existence across factors measuring individual-, market- and industry-specific characteristics using ordinary least squares. Results suggest clear evidence of a declining speed of learning over time, which is also in consonance with the framework of Bayesian learning. Results across the groups remain the same even after controlling for survivorship bias. I conclude that a higher speed of learning is not necessarily a good thing, because speed of learning is contingent on the entrepreneur's initial knowledge and the precision of the signals he receives from the market. Also, there is no reason to expect speed of learning to be related to the growth of the firm in one direction over another.

Jelcodes:D84,M13

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ABSTRACT

Building on the model developed by Parker (2006), I inquire whether a higher entrepreneurial speed of learning is desirable, and whether there is a linkage between the speed of learning, which is specific to the entrepreneur and the rate of growth shown by the firm? Using the Kauffman Firm Survey, changes in the speed of learning are measured for the initial six years of the firm's existence across factors measuring individual-, market- and industry-specific characteristics using ordinary least squares. Results suggest clear evidence of a declining speed of learning over time, which is also in consonance with the framework of Bayesian learning. Results across the groups remain the same even after controlling for survivorship bias. I conclude that a higher speed of learning is not necessarily a good thing, because speed of learning is contingent on the entrepreneur's initial knowledge and the precision of the signals he receives from the market. Also, there is no reason to expect speed of learning to be related to the growth of the firm in one direction over another.

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INTRODUCTION

Researchers have shown that there is evidence of an entrepreneur learning the tricks of the trade as the time passes. Efficient entrepreneurs identify the opportunities offered by the market, which gets reflected in the growth of the business. Building on this evidence, it becomes crucial to identify how fast an entrepreneur learns and adjusts his beliefs to the newer information and signals received from the environment, and if an entrepreneur learns faster, does he generate better results for the business? If these newer beliefs do not bring any advantage to the organization, then why should an entrepreneur update his opinion based on new signals? These questions are unraveled by building on the model of entrepreneurial learning developed by Parker (2006). In this study I investigate whether the speed of entrepreneurial learning is same across time and across groups, and whether firm growth is altered by this learning. While the focus of the study is on capturing the speed of learning, it also explores the linkages between learning, growth and firm survival.

Parker using an adaptive expectations approach finds that entrepreneurs assign more weight to the prior beliefs, and provides evidence of differences in speed of learning across groups. However, he treats speed of learning to be constant and presents little evidence on how the speed of learning evolves with the age of the firm. In contrast, using a Bayesian framework I present a theoretical evidence of declining speed of learning, which is also in consonance with the empirical findings.

Parker seeks to determine the speed of entrepreneurial learning captured through a change in effort level expended in the business. Using an adaptive expectations approach, he builds a model of entrepreneurial learning where an entrepreneur supplies effort and forms an expectation of his effort's unobserved productivity for the next period. The entrepreneur only receives noisy signals about the productivity, so learning takes time. The reason for this is that outcomes associated with the effort are known to an entrepreneur only at the end of the period. This leaves him with an option to form an expectation about the productivity that his level of effort generates. The current effort and expectation of unobserved productivity together gets translated into the firm's earnings.

Further, Parker's model suggests that an entrepreneur's future actions are based on the asymmetry between expectations he formed in the previous period and the market signals he receives in the real time. If there is no divergence between the expectations and the noisy signals, he maintains the status quo, which is an elusive state to believe. However, if the expectations formed exceed the signals, he will update his beliefs about the unobserved productivity and decrease the effort supplied in the next period. In contrast, if signals are greater than the expectations, he will update the unobserved productivity in a way that will increase the future work effort. The newer effort level will further affect the earnings in the next period. This continuous updating process in the light of new information captures the speed with which an entrepreneur responds to the newer signals. Therefore, future prospects depend on how effectively an entrepreneur processes new, volatile and costly signals that he receives from the environment (Casson, 2005). Levinthal mentions that this adaptive exchange with the environment changes the behavior of an entrepreneur that further leads to "specialization" (1996: 26-27). The methodology of adaptive expectations even allows for arbitrary choices, which are updated based on the signals an entrepreneur receives (Marcet & Nicolini, 2003; Milani, 2007; Politis, 2005).

Parker uses weekly hours expended into the business by an owner as a measure of work effort. He uses a two year data from the British Household Panel Survey and finds that entrepreneurs adjust their beliefs by 16% when they receive newer signals. He refers to this as, "the extent to which entrepreneurs exploit new information when updating their expectations" (2006: 7). In other words, entrepreneurs assign lesser weight to the newer information and more to his older beliefs. He finds that there are no significant differences in the speed of learning between male and female entrepreneurs, and between employers and non-employer firms. However, he finds that younger entrepreneurs significantly assign a higher weight to the newer signals as compared to the older entrepreneurs.

Parker treats the speed of learning (which he captures through λ, see section 2 for a detailed analysis) as a constant, which captures how an entrepreneur assigns weights between the past beliefs and the new signals. In his analysis there is little evidence of how speed of learning evolves over time. This weighing process, if analyzed over a longer period of time, will reveal how the mix of weights between newer and prior beliefs evolves. To exactly capture this weighing trend empirically, I use six year confidential micro-data provided by the Kauffman Firm Survey (KFS) through the National Opinion Research Center (NORC) data enclave for the analysis. Following the methodology specified by Parker, learning speed is calculated using Ordinary Least Squares (OLS) in repeated cross-sections. For a six year data, I estimate five parameters depicting the speed. I seek to examine existence of a clear pattern between the weights over a period longer than two years. A clear declining trend is witnessed over the six years of analysis, where entrepreneurs assign lesser weight to the newer signals each year and more to the prior beliefs.

This evidence is in consonance with the set-up of Bayesian learning where it is known that the speed of learning declines with the age of the firm. There is less information to extract from the noisy signals, which an entrepreneur receives as the business gets older. Bayesian learning formulates learning in a framework where an entrepreneur is not fully informed and updates his beliefs using a Bayesian learning rule. The initial beliefs in the Bayesian learning are termed as “prior”, which are revised contingent on the events that yields an updated or modified uncertainty known as “posterior.” This whole process is known as “updating a prior” because the posterior in the current stage will act as a prior to the next stage (Albert, 2001: 2). Linking it to this study, there is clear evidence that the posterior beliefs that an entrepreneur deciphers from the expectation of the unobserved productivity, carry less weight each year. This declining weight leads to a decline in the speed of learning. So, as the firm gets older, less weight is assigned to the newer information, and it suggests a Bayesian model rather than the adaptive expectations model written by Parker.

Further, it is not possible to test for the survivorship bias in Parker's study. It is possible that firms that survive a longer period display a higher speed of learning. To account for survivorship bias, I look into two scenarios. In the first case, accounting for firm attrition, I calculate the speed of learning for those firms that survived all six years. In the second case, the entire sample is considered. Pooled OLS estimator is used to calculate the differences in learning across the groups. Six categories are defined on the basis of individual-, market- and industry-specific factors. These are: gender, age, primary location of the business, whether firm has employees, technology level, and legal status. Cross-section of firms displays a similar result under both the scenarios providing evidence for no survivorship bias.

One of the missing pieces from Parker's study is whether the speed of learning alters the firm's performance. If an entrepreneur is quick in imbibing the signals and acts fast, it is of further interest to determine its impact on the firm's performance. Is there a clear one to one mapping of higher speed of learning to superior firm performance? Or is the speed of learning just a response variable that only captures the volatility in the work effort and has no relation to the firm's growth. Therefore, to test for relation between the entrepreneurial speed of learning and firm's growth, return on assets is calculated for the firms that survived all six years and is compared with the speed of learning. Empirical results provide evidence of no clear linkage between the two variables. Firms with higher speed of learning are not necessarily high growth or better performing firms.

The above result should be interpreted with caution because firms with slow speed of learning are the firms which perform better in terms of growth and survival. There is a clear linkage between survival rate and firm growth. Firms which survived the entire six year period show a higher rate of return on assets. A longer spell is favorable for the growth of the firms. The reason for this can be ascribed to the fact that, with the age, firm productivity level improves (Irwin & Klenow, 1994). Better productivity gets translated into a higher growth rate. There is research exploring the intricate relation between firm age, survival and growth. While some studies point towards the fact that the relation between these factors vary across industries among start-ups (Dunne et al., 1989), some ascribe this to the ability of a firm to adapt to the ever changing business environment (Geroski, 1995), and some have even pointed that, “entrants that are able to survive exhibit higher growth rates” (Audretsch, 1995: 1). These results are confirmed for the sample under consideration.

There are three implications from the above discussion. First, the speed of learning declines with the time. The noisy signals carry less weight and each set of newer information is less important to the entrepreneur. It should be noted the firms in this data-set are start-ups and are in their sixth year of existence. While there is more to learn in the initial years, the need to assign more weight to the market signals goes down when a business is firmly established. This fact is even supported within the framework of Bayesian learning. An entrepreneur then relies on his past behavior to steer him towards the path of success. This analysis has some policy implications for the organizations that train and assist business start-ups. It is advisable to guide and assist the start-ups in the initial couple of years when entrepreneurs are open to the concept of learning and assign more weight to the market signals. Assistance in the form of policy programs does affect the venture performance (Roper & Hart, 2005). Because an entrepreneur's past and current beliefs are not processed in isolation. There is interdependency between these beliefs and actions that guide an entrepreneur and builds his future beliefs (Minniti & Bygrave, 2001).

Second, differentials in the speed of learning across groups do not suggest superiority of one group over another. In this study, there is clear evidence of a significant higher speed of learning for firms operating from the rental location as compared to firms operating from home. Similarly, firms with employees and firms that are established as corporations have a higher speed of learning. However, this does not imply that the firms with higher speed of learning are better than the comparison groups. Considering two cases, (i) let us assume that firms operating from home and rental spaces both share the same level of information to begin with, but firms in rental spaces have access to more precise current market signals than firms operating from home. It seems that firms in rental location are better than the ones which operate from the home.

However, firms operating from rental offices learn faster because the new information they receive is more precise and they know more than the other group to begin with; (ii) let us assume that if firms operating from rental location knows less to begin with, and both groups receive current market signals with the same precision, it can be inferred that firms in the rental location are not good performers. They show a higher speed of learning because they have more to learn in order to catch up to the level of firms operating from home. Therefore, a higher speed of learning is not necessarily a good thing. Even with a higher speed of learning, one group could be better or worse than the other. To gain evidence of the result from Bayesian learning, further analysis in this study explores the linkage between higher speed of learning and firm growth that is explained in the next point.

Third, empirical analysis suggests that a higher speed of learning does not alter a firm's growth rate. It can be inferred that even if an entrepreneur assigns more weight to the noisy market signals, it does not mean that this will be reflected in the firm's performance. It could be that each additional signal an entrepreneur receives is not worth the prior signal. This means that future signals are not as informative for the entrepreneur in the later stages, and therefore does not get translated into the performance of the business. If group A shows a higher speed of learning as compared to group B, in this framework it would mean that entrepreneurs in group A assign a higher weight to the market signals as compared to group B. Furthermore, if growth rate for group B is greater than group A, this would simply mean that the prior beliefs held by group B entrepreneurs are more informative than the market signals that are received by group A.

The above perspective points towards the fact that the speed of learning tends to decline with the age of the firm. However, this learning does not modify a firm's growth. This result should be interpreted with caution because assigning less weight to the newer signals does not imply that there is no learning, in fact an entrepreneur with time learns to identify relative worth of each signal and assigns weights accordingly. This result is in consonance with the fact that firm's with slow speed of learning show a higher survival rate and also a higher growth rate. Past beliefs formed over this updating process serve as an important referral point, and these beliefs are further reflected into higher survival and growth rate. Results are interpreted in the light of Bayesian framework rather than adaptive expectations approach adopted by Parker.

The remainder of this paper is organized as follows. Section 2 explains Parker's model of learning. Section 3 describes the data-set used for this study and how variables are constructed. Section 4 presents the empirical estimation of speed of learning across -years and -groups. It further presents evidence for results by interpreting them in light of Bayesian framework, followed by exploring the linkage between the speed of learning and the firm growth. Section 5 presents the conclusion of the study.

ENTREPRENEURIAL LEARNING

Accurate information on what affects a firm's performance and makes entrepreneurs successful is important in formulating policy programs. This is even more relevant in case of business start-ups where it is tough to survive the initial couple of years, and even tougher to achieve a respectable growth rate. The initial years of start-ups define future growth trajectory. An entrepreneur who can promptly identify the market signals in the initial years will be better equipped to recognize the opportunities and deal with the macro-economic shocks. “Starting a new business is essentially an experiment...which can be tested by experience” (Block & McMillan, 1985). This experimentation leads to a process of learning and re-learning (Petkova, 2009), which improves the entrepreneur's repertoire of ready references to be used in the future when he faces similar situations. Therefore, history does matter (Arthur, 1989), but to what extent will an entrepreneur be willing to rely on his past while making current decisions? And what about the situations in which he has no reference, as generally witnessed in business start-ups? Factors which affect entrepreneurial learning are deemed important, yet they are poorly understood, leaving us uninformed about its empirical measurement. Using adaptive expectations approach, Parker determines the speed of learning by capturing the weighing process followed by an entrepreneur, which is explained in the next sub-section.

Parker's model of entrepreneurial learning

Parker follows an adaptive expectations framework, where an entrepreneur forms an expectation that is based on his past experience. An updating process changes these expectations over a period of time, correcting for the systematic forecasting error. In his study, an entrepreneur supplies effort that is captured through hours worked per week in the business, h_{it}. Entrepreneur's ability, the market status, and a stochastic component determine his productivity level. This stochastic component makes the true productivity level indeterminable, which leaves an entrepreneur to form an expectation about the “unobserved productivity” in the next period. It should be noted that the earnings of the firm gets affected by this unobserved productivity via effort level supplied by an entrepreneur. This justifies forming correct expectations that help an owner to make apt judgments about the effort he is going to supply in the next period. This updating process captures the speed with which an entrepreneur changes his prior beliefs and determines weight to be assigned to the noisy signals.

Considering the labor supply models, there is enough research in the area of hours expended by the employees and its impact on their productivity (Blundell & MaCurdy, 1999).

The main issue in analyzing the work effort by the workers of a firm is to determine the wage bill to be disbursed. In case of owners, effort exerted has a broader impact not only on the firm's current performance, but also on its future growth. In this paper, hours worked by an owner, help in constructing an index of entrepreneurial learning.

In Parker's model, an entrepreneur i tries to maximize a linear utility function $U(\Pi_{it}, c_{it})$ at time *t:*

$$U = U(\Pi_{it}, c_{it}) = \Pi_{it} - c_{it}, \tag{1}$$

where, Π_{it} is the weekly net operating profit and c_{it} is the non-pecuniary cost of effort supplied by the entrepreneur, which takes the form of a Stone-Geary convex cost function:

$$c_{it} = (2\gamma)^{-1} \left(h_{it-1} - \underline{H}\right)^2, \tag{2}$$

where, $\gamma > 0, \underline{H} \geq 0$ are both parameters and entrepreneurs dislike working beyond $\underline{H}$. True unobserved productivity, p_{it}, is defined as the ratio of output (current revenue) to input (effort exerted in the last period, i.e. lag hours, h_{it-1}). Combining the signal of unobserved productivity and normalizing the output to one, productivity becomes, $\hat{p}_{it} = {}^{1}/_{h_{it-1}}$, and signal for revenue can be extracted as, $1 = \hat{p}_{it}. h_{it-1}$. Pecuniary operating costs take the form$\phi_{it}. h_{it-1}$, where ϕ_{it}, is the marginal operating cost and consists of two parts, an individual specific marginal cost, ϕ_i, and a stochastic component, ϵ_t. It is assumed that ϕ_i is known to an entrepreneur with certainty and $E(\epsilon_t) = 0$. Therefore, operating profits are

$$\Pi_{it} = \hat{p}_{it}. h_{it-1} - \phi_{it}. h_{it-1}, \tag{3}$$

from which the signal, $\hat{p}_{it}$, can be obtained:

$$\hat{p}_{it} = \frac{\Pi_{it}}{h_{it-1}} + \phi_{it}. \tag{4}$$

To determine the effort to be exerted in the next period, an entrepreneur forms an expectation of his true unobserved productivity, p_{it}, that is based on the information set, Ω_{it}, available to him at time *t*, and the signals an entrepreneur receives for his future unobserved productivity, $\hat{p}_{it+1}$, as described in equation (4). This yield

$$E(\hat{p}_{it+1}|\Omega_{it}) = E(\hat{p}_{it}|\Omega_{it}). \tag{5}$$

The information set at time *t* is the union of past information set available at time *t-1* and the productivity signal at time *t*. The entrepreneur continuously interacts with his environment and receives new signals about the effort he supplies. This process helps him in updating his beliefs, which in part comes from the newer signals and in part from his prior beliefs. The updating process finally leads to learning about the true state of nature, if $\lambda > 0$, leading to the following assumption:

$$E(\hat{p}_{it}|\Omega_{it}) = E(\hat{p}_{it-1}|\Omega_{it-1}) + \lambda[\hat{p}_{it} - E(\hat{p}_{it-1}|\Omega_{it-1})], \qquad 0 \leq \lambda \leq 1 \tag{6}$$

where, $\lambda \in [0,1]$ in equation (6) is a parameter that captures the speed of learning, or as Parker terms it, "the extent to which entrepreneurs exploit new information when updating their expectations." Generally, an entrepreneur's expectation of the unobserved productivity in period *t-1*, $E(\hat{p}_{it-1}|\Omega_{it-1})$, and the signals which he receives from the market for his unobserved productivity in period *t*, $\hat{p}_{it}$, will not be same. There is bound to be a difference between the two which is captured by λ in equation (6).

In equation (6), if $\lambda = 0$, then (6) reduces to $E(\hat{p}_{it}|\Omega_{it}) = E(\hat{p}_{it-1}|\Omega_{it-1})$, which implies that the entrepreneur assigns all weight to his prior beliefs and does not learn from the noisy market signals. If $\lambda = 1$, then (6) reduces to $E(\hat{p}_{it}|\Omega_{it}) = \hat{p}_{it}$, which implies that the entrepreneur assigns all weight to the noisy market signals. In this updating process, one can get intermediate values of λ, which implies that an entrepreneur tries to create a mix between noisy signals and the prior beliefs. The new expectation of true unobserved productivity from (6) further guides an entrepreneur to decide on his effort level to be supplied in the next period. If his expectation of returns in the form of earnings has increased, he will exert more effort in period *t+1*. The effort level that maximizes expected net revenue can be calculated as:

$$h_{it} = \gamma E(p_{it}|\Omega_{it}) - \gamma\phi_i + \underline{H}, \tag{7}$$

As $\gamma > 0$, there is a positive relation between the expected productivity and effort. Substituting the values of $E(p_{it}|\Omega_{it})$ in the above equation generates the regression equation from which we can estimate λ:

$$h_{it} = \alpha + (1-\lambda)h_{it-1} + \gamma\lambda\left(\frac{\Pi_{it}}{h_{it-1}}\right) + \mu_{it}. \tag{8}$$

In equation (8), h_{it} is the hours worked in period t, $\alpha = \lambda\,\underline{H}$ and is a positive constant, $\frac{\Pi_{it}}{h_{it-1}}$ is the profit to lagged hours ratio, and μ_{it} is an error term with mean zero.

Following Parker, equation (8) is estimated in the repeated cross-sections for the entire sample and then a group wise analysis is conducted where lag hours and profit to lag hour ratio is interacted with a dummy variable. This dummy variable indicates membership of specific firm into the group or otherwise. The next section describes the data and how the variables are constructed.

SAMPLE DESCRIPTION

Data-set

I use confidential micro-data provided by the KFS through the National Opinion Research Center (NORC) data enclave. The KFS is a panel data-set on 4,928 firms, all of which began operations in 2004. At the end of the project, the KFS will contain detailed data spanning over a time frame of 2004-2013. The base line survey was conducted in 2004, and since then there have been five follow-ups. The sample size has declined over these years for a number of reasons including problems in locating a firm in the follow up periods, non-responses, or because the firm closed down. One of the major advantages of the KFS is that it does not suffer from inherent survivor bias, because all the firms started at the same time (Smith, 2010). In the survey, for a firm to be considered as a start-up it must have satisfied at least one of the following five criteria in 2004: (i) it paid state unemployment taxes, (ii) it paid Federal Insurance Contributions Act (FICA) Taxes, (iii) it had a legal status, (iv) it used an Employer Identification Number EIN, or (v) it used schedule C to report business income. A firm is excluded from the survey if it reports any of the above five criteria prior to 2004 (Robb et al., 2009).

To ensure that only start-ups are included in the survey, owners were asked to report whether the business (i) was started as a new business, branch or a subsidiary owned by an existing business, (ii) was inherited, (iii) was started as a new independent business, (iv) was purchased as an existing business, (v) was purchased as a franchise or, (vi) was an organization designed for social and charitable objectives and established as “non-profit”. If the responses fell under category (i), (ii) or (vi), respondents were excluded from the sample (Robb et al., 2009, 2010). I focus on data collected in the first six years of a firm's existence (calendar years 2004-2009). To account for attrition bias, I conduct two sets of analyses: in the first set the entire sample is included and in the second, firms that did not survive the entire six year period are excluded.

Using a positive sorting on hours worked, work experience, equity and education, the main owner[1] is identified. If there is a tie in number of hours worked, work experience is used to resolve that tie. Further ties are resolved on the basis of maximum education and equity share. As a result of this rank ordering, gender, age and ethnic origin of the main owner is clearly identifiable. Accordingly, 2,082 firms are excluded from the sample as they reported no owner for consecutively four years. Further, 217 firms are dropped from the sample because they reported no revenue in all these years. For these firms their level of sales, revenue, and profit, are cross-checked and zero values are found for these variables. The final sample size consists of 3,061 firms.

Variable construction

Dependent Variable. Effort exerted by an entrepreneur is the dependent variable and is defined as hours worked per week at the business, h_{it}.

Independent Variables. Lag hours worked by the owner and ratio of weekly net operating profit to lag hours are used as independent variables. To calculate the weekly net operating profit, Π_{it}, annual net operating profit reported in the survey is divided by 52. To calculate the differences in learning between groups, six groups are defined on the basis of individual-, market- and industry-specific factors. These are: gender, age, primary location of business, whether the firm has employees, technology level, and legal status. Detailed descriptions of the groups are provided in Table A1.

[1] Owner has been defined as a person who is actively involved in running the business

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Owner-specific categorization. Learning differentials are recorded for male and female entrepreneurs with the help of first categorization. In the baseline survey of 2004, approximately 69% of the firms had men as the owner, which continued even in 2008 with a slight decrease in the percentage to 68%. However in the constructed sample, firms with male entrepreneurs have a slightly higher survival rate.

Similarly, one of the important facets that affect the speed of learning is the age of an entrepreneur. With a modal age of 41, entrepreneurs older than 41 are categorized as "older" and if the age is less than 41, they are categorized as "younger". In the case of older entrepreneurs, past behavior can act as a ready reference, whereas in the case of younger entrepreneurs, where there is a lack of ready set of references, it is more likely that they will assign more weight to the current market signals. This makes it interesting to measure the differences in the learning parameter for younger and older entrepreneurs.

Firm specific categorization. It is also interesting to observe the linkage between the location of primary businesses and hours expended. If an entrepreneur can operate from the home, one can argue that he may put in less number of hours. In 2004, approximately 50% of the firms were home-based businesses. This number declined to 48.9% in 2007, after some where entrepreneurs moved their businesses from residential houses to a rented place or other location. This could be guided by the motivation of expanding the business and/or moving closer to customers.

Another interesting feature to look into is that whether a firm's “employer status” changes the way an entrepreneur reacts to the market signals. Similarly, the legal status of the firm might generate differences in the way entrepreneurs assign the weights to the prior beliefs and market signals. One of the reasons for the difference could be that firms established as corporations face a lot more legal obligations as compared to the firms operating as sole proprietorship, making them more alert about the rules and regulations, thereby assigning a higher weight on the market signals.

Industry specific categorization. The nature of the industry in which a firm operates also affects an entrepreneur's ability to learn. Generally, high-technology companies are considered to infuse more number of newer technologies and products into the market as compared to non-high-technology sector firms, which could imply that entrepreneurs of high-technology firms react faster than non-high technology firm entrepreneurs. However, one can also argue that firms that are not technology oriented have a lot more to learn regarding the market and update their level of technology. With oversampled high-technology firms in the data, industries have been classified as high-, medium-, low- technology industries. Two part strategy of matching the North American Industrial Classification System (NAICS) with the Hecker's (2005) is used for the classification of firms. The next section explains the empirical results across-years and groups.

EMPIRICAL ESTIMATION

Estimation across years

Equation (8) is estimated using OLS in repeated cross-sections that generate five values of λ, each value based on changes in hours worked over two contiguous years. Figure B1 and B2 shows the path of two λs, one for surviving firms and another one for the entire sample of firms. It is evident that λ follows a downward trend in both the cases, and there are minor differences between the paths of λ for the two groups. It can be inferred that over a period of time the speed of learning tends to decline. The value of λ for the entire sample figure B1, starts from 29.8% in the base year and then declines to 25.2% in the second year, in the third and fourth years it decreases to 18.8% and 17.5%, and has a value of 16.7% in the final year (see table A2). Recognizing the survey nature of the data, survey commands have been used for the analysis and therefore all the tables report linearized standard errors.

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It is interesting to observe that Parker estimated λ to be 16% from a single cross-section and firms with differing ages, suggesting that there is a little impact of newer information on entrepreneurs. In the initial years of firm's existence, there is plethora of new information to be absorbed and assimilated by an entrepreneur that yields the maximum learning. As the time elapses and an entrepreneur is fine tuned to the demands and expectations of the business, additional learning tends to decline. Therefore, beliefs that affect the learning process may either lose or gain their influence over time (Bullard & Duffy, 1999; Dawid, 1999; Minniti & Bygrave, 2001).

Table A2 gives a detail account of variation in λ over six years for the entire sample and table A3 lists the values of λ for the firms which survived six years. These results are presented over owner-, firm- and industry-specific groups and same declining trend is observed (also see figure B3). The value of λ is significant at 1% level in each year. Further λs are tested for significance across years using a Wald test and found to be significant.

Table A2 and A3 provide the year-specific results. To analyze how different groups react to the market signals and alter their speed of learning, a pooled OLS estimator is calculated by estimating equation (8). The values of λ from the pooled OLS estimator for groups lie in the same range as for the year-specific case. The results are tested for significance using an adjusted Wald test. Table 4 shows that same results are obtained when the survivor bias is not corrected and the results are calculated over groups for surviving firms, and when survivor bias is considered and overall sample is considered into the analysis. There is no evidence of a difference in learning rates. These results are discussed in the next section.

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Estimation across groups

Except for the firm-specific categorization, none of the groups show an evidence of significant differences in learning rates between groups. Considering the firm-specific categorization, businesses located in the rented space, firms which have employees working in it, and firms established as corporations show a higher speed of learning as compared to their counterparts. Home as a business location with no employees adds flexibility to the working schedule of an entrepreneur that might make him complacent. In addition, home based businesses are established as sole proprietorships. In this study, 21% of the firms are established as sole proprietorships and are located in the home, compared with only 11% of the firms established as corporations. Having employees as a support system and established as a corporation makes an entrepreneur more active that makes him assign a higher weight to the market signals. There is evidence that the choice of legal status with which a firm is established speaks a lot about the long term goals of the owner (Frankish et al. 2007), where firms established as corporations have a higher growth targets. This could be because hiring people and working as a corporation generates an expectation that entrepreneur should at least be familiar with labor and corporate laws. To illustrate, if a firm operates as a corporation which produces chemicals, then providing a safe working environment to his employees is a legal requirement. This puts an extra pressure on the owner which is reflected in assigning a higher weight to the current market signals.

Considering the owner-specific sub-group, speed of learning is higher for younger entrepreneurs; however, the results are not significant. An older entrepreneur would probably have a repertoire of references that he gained from his past beliefs and/or experiences, making him less amenable to the current market signals. In contrast, when it comes to the entrepreneurs who are young and at the same time new in business, they would assign more weight on the market signals, thereby leaving them with a higher speed of learning.

Analyzing the results over the gender differentials yield mixed results. For the surviving firms, female entrepreneurs show a higher speed of learning as compared to male entrepreneurs, whereas for the entire sample male entrepreneurs show a higher speed of learning. Despite the fact that firms with male entrepreneurs have a higher survival rate (86%) as compared to women entrepreneurs (82%), firms which survive all six years show a higher female entrepreneur speed of learning. This points towards the fact that women learn over a period of time and for the successful firms, which survived the first six years, women assigned a higher weight to the market signals as compared to men.

Further, firms operating in low-tech industries generate a higher speed of learning. One of the reasons for the speed of learning to be lower in the high-technology industry is cited by Baloff (1971). He suggests that there are two stages of learning, in the initial phase a firm begins the manufacturing process and reaches a point when there is no further learning that leads to "plateauing in the learning curve". Yelle (2007) mentions that, firms which are more "machine-intensive" have a higher ratio of machine to total labor and a lower progress ratio. Moreover Klenow (1998) in his research on learning- by- doing mentions that, "the more production experience the firm has with a technology, the less it has left to learn". This explains a higher speed of learning for firms in low-tech industries.

To check for robustness of results, a variation in the utility and cost function with a non-linear functional form is tested for. It should be noted that the same methodology is followed to test for non-linearity in the utility function as adopted by Parker. Up to six powers of Taylor approximation is tested for and there is no evidence of non-linearity even in this data-set and the linear functional form is a robust specification. Starting with $j=2, 3...5$, the coefficients are not significantly different from zero.

The above mentioned analysis displays a declining speed of learning. However, the adaptive expectations model presented by Parker treats λ to be a constant that does not confirm with the above result. The next section provides evidence using a Bayesian learning framework, and proves that λ is not constant; rather it declines with the age of the firm.

Interpretation of results using Bayesian Framework

Interpreting the results in light of Bayesian framework, consider equation (7), which shows the effort level that maximizes the expected net revenue. Let $\bar{p}_{it}$ denote the expected value of p at time *t*, that is, $E(p_{it}|\Omega_{it})$. Equation (7) can be rewritten as:

$$Eh_{it} = \gamma\bar{p}_{it} - \gamma\,\phi_i + \underline{H}. \tag{9}$$

Equation (5) and (9) yield the following profit equation for an entrepreneur *i*:

$$\Pi_{it} = \gamma\, p_t\, \bar{p}_t - \gamma\, \bar{p}_t\phi_t, \tag{10}$$

If ϕ_i is known to an entrepreneur with certainty, then he would immediately learn the true productivity, p. However, as there is noise associated with the marginal operating cost of effort, an entrepreneur can only observe a signal, $z_t = p + \varepsilon_t$, where $var\,(\varepsilon_t) = \sigma^2$. Suppose that *i's* prior belief about the true productivity, *p*, is that it is a draw from a Normal distribution with mean θ and variance σ_θ^2; and that the signals, *z*, about *p* are random draws from a Normal distribution with mean *p* and variance σ^2. Let $\bar{z}_t$ denote the mean of the *t* signals observed up to period *t*. Using standard formulae for the normal conjugate family (DeGroot, 1970, p.166), *i's* posterior belief is Normal with mean

$$\bar{p}_t = \frac{\theta\sigma^2}{\sigma^2 + t\sigma_\theta^2} + \frac{\bar{z}_t\, t\sigma_\theta^2}{\sigma^2 + t\sigma_\theta^2}, \tag{11}$$

and variance

$$\sigma_t^2 = \frac{\sigma^2\sigma_\theta^2}{\sigma^2 + t\sigma_\theta^2}. \tag{12}$$

The variance of beliefs is a deterministic function of time; the pair $\{\bar{p}_t\,, t\}$ is a sufficient statistic for current beliefs. The evolution of beliefs over time can be described by a transition function (Easley & Kiefer, 1988: 1050) $b(z, \bar{p}_t, t)$ that maps a Normal distribution with mean $\bar{p}_t$ and variance σ_t^2, into a Normal distribution with mean

$$\bar{p}_{t+1} = \frac{\bar{p}_t \sigma^2 + z_{t+1}\, \sigma_{\mathrm{t}}^2}{\sigma^2 + \sigma_t^2}, \tag{13}$$

and variance

$$\sigma_{t+1}^2 = \frac{\sigma^2 \sigma_{\mathrm{t}}^2}{\sigma^2 + \sigma_t^2}. \tag{14}$$

It should be noted that $E[z_{t+1} \mid \bar{p}_t] = \bar{p}_t$ which implies that $E[\bar{p}_{t+1} \mid \bar{p}_t] = \bar{p}_t$ in equation (13). Equation (12) and (13) together yield the conditional variance of the subjective mean as

$$var(\bar{p}_{t+1} | \bar{p}_t) = \frac{\sigma^2 \sigma_\theta^4}{\left(\sigma^2 + (t+1)\sigma_\theta^2\right)^2}, \tag{15}$$

The variance of $\bar{p}_t$ declines as experience progresses at the rate $O(t^{-2})$. As the optimal amount of effort is linear in *t*, variance of h_t also declines at the rate $O(t^{-2})$. Therefore a simple Bayesian model predicts a declining variability in hours worked. To see it more precisely, rewriting equation (13) and substituting the value of σ_t^2 from (12) gives

$$\bar{p}_{t+1} = \frac{\bar{p}_t \sigma^2}{\sigma^2 + \sigma_t^2} + \frac{z_{t+1}\, \sigma_{\mathrm{t}}^2}{\sigma^2 + \sigma_t^2}, \tag{16}$$

$$\bar{p}_{t+1} = \frac{\bar{p}_t (\sigma^2 + t\sigma_\theta^2)}{\sigma^2 + (t+1)\sigma_\theta^2} + \frac{z_{t+1}\, \sigma_\theta^2}{\sigma^2 + (t+1)\sigma_\theta^2}. \tag{17}$$

The above expression explains that as the firm gets older (i.e., as t gets larger), less weight is put on the new information, and it suggests a Bayesian model rather than the adaptive expectations model written by Parker. Parker's framework would say beliefs take the form of an adaptive expectations rule and are like:

$$\bar{p}_{t+1} = (1-\lambda)\bar{p}_t + \lambda\, z_{t+1}. \tag{18}$$

Comparing equation (18) with the Bayesian framework in equation (17), it is interpreted that λ is not constant. Instead, (18) can be rewritten as:

$$\bar{p}_{t+1} = (1-\lambda_{t+1})\bar{p}_t + \lambda_{t+1}\, z_{t+1}. \tag{19}$$

Combining equation (17) and (19), after backdating them by one period gives an equation for λ, which is strictly decreasing in *t*.

$$\lambda_t = \frac{\sigma_\theta^2}{\sigma^2 + t\sigma_\theta^2}. \tag{20}$$

Therefore, the speed of learning is declining with the age of the firm. Interpreting the different rates of λ across at any given point in time, consider two groups, A and B. Assuming that group A has a higher estimated λ than group B can be good or bad news for group A. Consider two scenarios,

• If Group A has a higher variance for prior beliefs, σ_θ^2, but the same variance for the current signals, σ^2, this implies that group A has no more precise signals than group B, but it knows less to start with. This, one supposes is bad for group A. It only appears to learn faster because it initially knows less and therefore has more to learn. But group A is always inferior to group B because it always knows less. Linking it with the empirical findings, younger entrepreneur and entrepreneurs operating in low-tech industries know less to start with, resulting in a higher speed of learning. They are similar to group A in the example.

• If Group A has the same variance for prior beliefs, σ_θ^2, but a lower variance for the current signals, σ^2, this implies that group A has more precise signals than group B, but it initially knows exactly the same. This, one supposes, is good for group A. It learns faster because its new information is more precise. Group A always knows more than B in this case.

It can be inferred that a higher λ is not necessarily a good thing. Even with a higher λ , one group could be better or worse than other. Further to gain evidence of the result from the Bayesian learning, next section analyzes whether there is a relation between λ and firm growth. In other words, it examines whether a higher λ is reflected in the firm's performance.

Linkage with firm growth

To maintain uniformity, same cross-section of firms is used for measuring the firm growth as for the speed of learning. Relative growth percentage (from 2004 as the base year and 2009 as the final year) for each group is calculated rather than calculating the average growth rate over six years.

Growth rate is calculated only for surviving firms for the reason that these firms survived the initial hiccups which transpire with the "liability of newness" and "liability of smallness" (Gilbert et al., 2006). In this context Petrunia (2008), aptly remarks that, "it is difficult to know what growth persistence means for firms that exit an industry. Death is an absorbing state, so growth persistence is meaningless for exiting firms." Moreover the initial super high or low growth rates will not have any influence on the calculation of growth rates. It should be noted that there is no attempt to measure the determinants of growth in this study. The focus is on ascertaining the differentials in the growth rates over the cross-section of firms.

There is no unanimity on what constitutes growth of a firm which makes it even more crucial to specify the methodology used to measure it (Diambeidou et al., 2007; Korunka et al, 2011). Where increase in total assets might sound a viable option to measure growth for a firm involved in construction and manufacturing, it would be the least preferable variable to capture growth for a firm involved in services sector (see Dobbs & Hamilton, 2006). Researchers have used various measures to account for firm growth which range from increase in tangibles like total assets, sales, employees to intangibles like profit, return on assets employed and revenue (Davidsson et al., 2006; Delmar, 1997; Garnsey et al., 2006; Gilbert et al., 2006).

For this analysis, return on asset (ROA) is calculated to represent the firm growth rate as shown in equation (21). It measures the return per dollar over total assets that constitute a sum total of borrowed money and owner's equity. It accounts for the efficiency of the firm in addition to the profitability of the firm.

$$Return\ on\ Assets\ (ROA) = \frac{Net\ Earnings}{Total\ Assets}. \tag{21}$$

Let ROA_{ikt} represent the return on asset of i^{th} firm, belonging to a group k at time t, where i ∈ {Firms which survived six years} , and $t \in \{1, \ldots, 6\}$. The difference in ROA between $t=6$ and $t=1$ gives an absolute growth (G_{ikt}) as shown in equation (22) and relative growth rate (g_{ikt}) shown in equation (23).

$$G_{ikt} = ROA_{ikt=6} - ROA_{ikt=1}, \tag{22}$$

$$g_{ikt} = \frac{ROA_{ikt=6} - ROA_{ikt=1}}{ROA_{ikt=1}}. \tag{23}$$

ROA gives a comprehensive view which captures, debt, equity and profit, all in one. Analyzing the growth rate for the surviving firms, it is only for firm-specific categorization of employer firms that generate a higher speed of learning and a higher growth rate (see table A5). Except for this group, rest every other classification display no relation between the speed of learning and firm growth.

…………………………
Insert Table A5 about here
………………………..

However, there is clear evidence that firms with higher growth rate are the firms which survived more. To illustrate, owner-specific categories, men and older entrepreneurs show a higher growth rate and a higher survival rate, despite the fact that both these categorizations show a lower speed of learning. A similar result is observed for firms that are in medium technology industries. It should be noted that, longer surviving firms have a higher rate of growth, because irrespective of learning, productivity rises with firm's age (Irwin & Klenow, 1994). Therefore, the above analysis strengthens the result obtained earlier that there is no reason to expect λ could be related to performance in one direction over another.

CONCLUSION

One of the consistent and significant results from the above analysis is that speed of learning declines with the age of the firm. This feature is consistent with the framework of Bayesian learning where λ is not treated as constant; rather it is determined from the mix of prior beliefs and current signals. Parker's framework is based on adaptive expectations that treated λ as a constant and presented little evidence on the declining speed of learning.

Further, it is inferred that a higher speed of entrepreneurial learning is not desirable, and there is no reason to expect a positive relation between entrepreneurial leaning and firm growth in this framework. Instead, firm survival and growth rate are positively related. This result holds even after firm attrition has been taken into consideration. Even though there is no linkage between faster speed of learning and firm growth, policy intervention in the form of assistance to start-ups in the initial couple of years seems a plausible method to detect the under performers.

Capturing learning, in its true sense, is contingent on the correct estimates of signals an entrepreneur receives and his initial knowledge. Cassar and Craig mention that entrepreneurs who rely more on their past beliefs suffer from “hindsight bias” that affects their ability to make accurate decisions (2009: 150). It is likely that there are bound to be distortions and errors even while recalling the past information, which is thought to be more of a characteristic feature while decoding the current noisy market signals. Therefore, there is presence of an error component in both - forward looking approach of relying on current signals and backward looking framework of recalling past information from already established beliefs. The fact that how an entrepreneur extracts relevant information from each extra signal, and maintains a balance between past beliefs and current signals, captures his speed of learning.

Moreover, looking at the results intuitively, why would an entrepreneur assign increasing weights to the newer noisy market signals when he has already learned to extract the relevant information from past beliefs? If weights for newer signals increase this implies there is no permanent learning, with no formation of beliefs that could have served as a ready reference for the future. This structure of learning is reflected in the higher survival rate along with the firm's better performance. Identifying the worth of each new signal differentiates the true learning parameters of the entrepreneurs. As Casson, aptly pointed out that, an entrepreneur “learns from the deals that he makes, and he learns from the deals that fall through” (1982: 386). Therefore, in the first place, each owner receives a different set of signals from the market that differentiates their behavior and action. Even though entrepreneurs somehow receive the same information set, the processing and assimilating speed differs between them, which differentiate successful entrepreneurs from non-successful entrepreneurs (Frankish et al., 2007).

To conclude, true learning enables formation of correct estimates and segregation of good from bad signals. Assigning lesser weights to the newer signals does not imply that an entrepreneur is not learning. Past beliefs could be equally informative if the posterior belief was updated correctly in the light of newer information.

APPENDIX A: TABLES

TABLE A1: Description of Sub-Groups

Sub-group	Categorization	Description
Owner Specific		
Gender of the Owner	Female=1 Male=0	Female being the reference group
Age of the Owner	Older=1 Younger=0	Age > 41: Older (modal age)
Firm Specific		
Employer	Employer=1 Non Employer=0	Firm is an employer or not
Location of business	Home-Based=1 Rented=2 Other- Location=3	Describes location of the business space
Legal status	Sole-Proprietor=1 Corporation=2 Other Legal=3	Defines Legal status of the firm
Industry Specific		
Technology Level	Hi-tech=1 Med-tech=2 Low-tech=3	Firm belongs to which Industry

TABLE A2 All firms: OLS – Pooled and Group wise analysis

Groups	04-05	05-06	06-07	07-08	08-09	Significant within groups across years
Pooled	0.29# (0.01)	0.25# (0.01)	0.18# (0.01)	0.17# (0.01)	0.16# (0.01)	-
R^2	0.57	0.61	0.66	0.67	0.68	
Owner Specific						
Female	0.23# (0.03)	0.23# (0.02)	0.22# (0.03)	0.19# (0.02)	0.16# (0.02)	
Male	0.31# (0.02)	0.25# (0.01)	0.17# (0.01)	0.17# (0.01)	0.17# (0.01)	No
R^2	0.57	0.61	0.66	0.67	0.68	
Older	0.29# (0.02)	0.23# (0.01)	0.17# (0.01)	0.17# (0.01)	0.15# (0.01)	
Younger	0.32# (0.03)	0.28# (0.02)	0.20# (0.02)	0.18# (0.02)	0.19# (0.02)	No
R^2	0.57	0.61	0.66	0.67	0.68	
Firm -Specific						
Home Based	0.25# (0.02)	0.22# (0.01)	0.18# (0.01)	0.17# (0.01)	0.16# (0.01)	Yes #
R^2	0.57	0.61	0.66	0.67	0.69	
Rented	0.46# (0.03)	0.37# (0.02)	0.25# (0.02)	0.22# (0.02)	0.22# (0.03)	Yes#
R^2	0.58	0.62	0.66	0.67	0.69	
Other Location	0.22# (0.04)	0.23# (0.03)	0.21# (0.03)	0.19# (0.03)	0.18# (0.02)	No

R^2	0.57	0.61	0.66	0.67	0.68	
Employer	0.34# (0.02)	0.29# (0.01)	0.21# (0.01)	0.21# (0.02)	0.22# (0.02)	
Non Employer	0.24# (0.02)	0.22# (0.02)	0.18# (0.02)	0.16# (0.01)	0.15# (0.01)	Yes#
R^2	0.58	0.61	0.66	0.67	0.69	
Sole Proprietor	0.26# (0.57)	0.24# (0.03)	0.18# (0.03)	0.17# (0.03)	0.20# (0.02)	No
R^2	0.57	0.61	0.66	0.67	0.69	
Corporation	0.43# (0.04)	0.34# (0.03)	0.25# (0.03)	0.23# (0.03)	0.18# (0.02)	Yes#
R^2	0.58	0.61	0.66	0.67	0.69	
Other Legal	0.25# (0.02)	0.21# (0.01)	0.16# (0.02)	0.16# (0.02)	0.15# (0.02)	No
R^2	0.57	0.61	0.66	0.67	0.69	
Industry Specific						
Hi-tech	0.27# (0.04)	0.26# (0.03)	0.23# (0.03)	0.18# (0.03)	0.15# (0.03)	No
R^2	0.57	0.61	0.66	0.67	0.68	
Med-tech	0.28# (0.03)	0.24# (0.02)	0.21# (0.02)	0.18# (0.02)	0.14# (0.01)	No
R^2	0.57	0.61	0.66	0.67	0.68	
Low-tech	0.31# (0.04)	0.25# (0.03)	0.16# (0.03)	0.17# (0.03)	0.18# (0.02)	No
R^2	0.57	0.61	0.66	0.67	0.68	
N	1508	3061	2938	2719	2585	

Significance of lambda for each group is tested using a Wald Test.

Significance of lambda across years is tested using an Adjusted Wald test.

* p < .10

** p < .05

\# p < .01

TABLE A3: Surviving firms: OLS – Pooled and Group wise analysis

Groups	04-05	05-06	06-07	07-08	08-09	Significant within groups across years
Pooled	0.30# (0.02)	0.25# (0.01)	0.18# (0.01)	0.17# (0.01)	0.16# (0.01)	-
R^2	0.57	0.61	0.67	0.68	0.68	
Owner Specific						
Female	0.24# (0.03)	0.24# (0.03)	0.23# (0.03)	0.18# (0.03)	0.14# (0.02)	
Male	0.31# (0.02)	0.25# (0.01)	0.17# (0.01)	0.17# (0.01)	0.17# (0.01)	No
R^2	0.57	0.61	0.67	0.68	0.69	
Older	0.30# (0.02)	0.24# (0.01)	0.16# (0.01)	0.16# (0.01)	0.14# (0.01)	
Younger	0.31# (0.03)	0.27# (0.02)	0.21# (0.02)	0.19# (0.02)	0.19# (0.02)	No
R^2	0.57	0.61	0.67	0.68	0.68	
Firm -Specific						

Home Based	0.25# (0.02)	0.22# (0.02)	0.17# (0.02)	0.17# (0.01)	0.15# (0.01)	Yes #
R^2	0.57	0.62	0.67	0.68	0.68	
Rented	0.44# (0.03)	0.36# (0.02)	0.23# (0.02)	0.18# (0.02)	0.21# (0.03)	Yes#
R^2	0.58	0.62	0.67	0.68	0.68	
Other Location	0.22# (0.05)	0.23# (0.03)	0.20# (0.03)	0.19# (0.03)	0.19# (0.03)	Yes#
R^2	0.57	0.61	0.67	0.68	0.68	
Employer	0.36# (0.02)	0.29# (0.01)	0.20# (0.01)	0.19# (0.02)	0.21# (0.02)	
Non Employer	0.23# (0.03)	0.22# (0.02)	0.18# (0.02)	0.16# (0.02)	0.15# (0.01)	Yes#
R^2	0.58	0.62	0.67	0.68	0.69	
Sole Proprietor	0.26# (0.30)	0.24# (0.02)	0.18# (0.02)	0.16# (0.02)	0.19# (0.02)	No
R^2	0.57	0.61	0.67	0.68	0.68	
Corporation	0.42# (0.04)	0.33# (0.03)	0.25# (0.02)	0.22# (0.03)	0.17# (0.02)	Yes#
R^2	0.58	0.61	0.66	0.67	0.69	
Other Legal	0.25# (0.03)	0.22# (0.02)	0.15# (0.02)	0.15# (0.02)	0.14# (0.01)	No
R^2	0.57	0.61	0.67	0.68	0.68	
Industry Specific						
Hi-tech	0.30# (0.05)	0.30# (0.04)	0.26# (0.03)	0.17# (0.03)	0.13# (0.03)	No
R^2	0.57	0.61	0.67	0.68	0.68	
Med-tech	0.26# (0.03)	0.22# (0.02)	0.21# (0.02)	0.18# (0.02)	0.14# (0.02)	No
R^2	0.57	0.61	0.67	0.68	0.68	
Low-tech	0.32# (0.02)	0.25# (0.01)	0.15# (0.01)	0.16# (0.01)	0.18# (0.01)	Yes#
R^2	0.57	0.61	0.67	0.68	0.68	
N	1295	2661	2617	2448	2432	

Significance of lambda for each group is tested using a Wald Test.

Significance of lambda across years is tested using an Adjusted Wald test.

* p < .10

** p < .05

# p < .01

TABLE A4: Comparison of surviving firms and entire sample using Pooled OLS Estimator

Groups	Surviving Firms :λ	Significance across groups	All firms: λ	Significance across groups
Pooled	0.20# (0.01)	-	0.21# (0.01)	-
R^2	0.65		0.65	
Owner Specific				
Female	0.21# (0.02)		0.29# (0.03)	
Male	0.20#	No	0.21#	No

	(0.01)		(0.01)	
R^2	0.65		0.65	
Older	0.20#		0.20#	
	(0.01)		(0.01)	
Younger	0.21#	No	0.21#	No
	(0.02)		(0.02)	
R^2	0.65		0.65	
Firm Specific				
Home Based	0.18# (0.01)	Yes *	0.18# (0.01)	Yes *
R^2	0.65		0.65	
Rented	0.28# (0.02)	Yes*	0.28# (0.02)	Yes*
R^2	0.65		0.65	
Other Location	0.20# (0.02)	No	0.21# (0.02)	No
R^2	0.65		0.65	
Employer	0.25#		0.25#	
	(0.01)		(0.01)	
Non Employer	0.18# (0.01)	Yes**	0.18# (0.01)	Yes**
R^2	0.65		0.65	
Sole Proprietor	0.20# (0.01)	No	0.20# (0.01)	No
R^2	0.65		0.65	
Corporation	0.30# (0.02)	Yes#	0.29# (0.02)	Yes#
R^2	0.65		0.65	
Other Legal	0.16# (0.01)	Yes*	0.17# (0.01)	Yes *
R^2	0.65		0.65	
Industry- Specific				
Hi-tech	0.20# (0.02)	No	0.19# (0.02)	No
R^2	0.65		0.65	
Med-tech	0.20# (0.01)	No	0.20# (0.01)	No
R^2	0.65		0.65	
Low-tech	0.20# (0.01)	No	0.21# (0.01)	No
R^2	0.65		0.65	
N	1295		2617	

Significance of lambda for each group is tested using a Wald Test.

Significance of lambda across years is tested using an Adjusted Wald test.

* $p < .10$

** $p < .05$

# $p < .01$

TABLE A5: Comparison of learning speed, growth rate & rate of survival: Surviving firms

Groups	Speed of learning: λ	Growth rate: Return on Asset	Speed of learning higher for which group?	Return on asset higher for which group?	Survival rate higher for which group?
Owner Specific					
Female Male	0.21 0.20	2.64 9.23	Female	Male	Male
Older Younger	0.20 0.21	7.99 7.15	Younger	Older	Older
Firm-Specific					
Home Based Rented Other Location	0.18 0.28 0.20	4.06 11.83 12.13	Rented#	Other Location	Other Location
Employer Non Employer	0.25 0.18	7.99 7.33	Employer **	Employer	Employer
Sole Proprietor Corporation Other Legal	0.20 0.30 0.16	5.39 8.44 9.69	Corporation#	Corporation	Other Legal
Industry-Specific					
Hi-tech Med-tech Low-tech	0.20 0.20 0.20	0.48 10.38 7.59	Low-tech	Med-tech	Med-tech

* p < .10

** p < .05

# p < .01

APPENDIX B: FIGURES

Figure B1: Speed of Learning for the Entire Sample

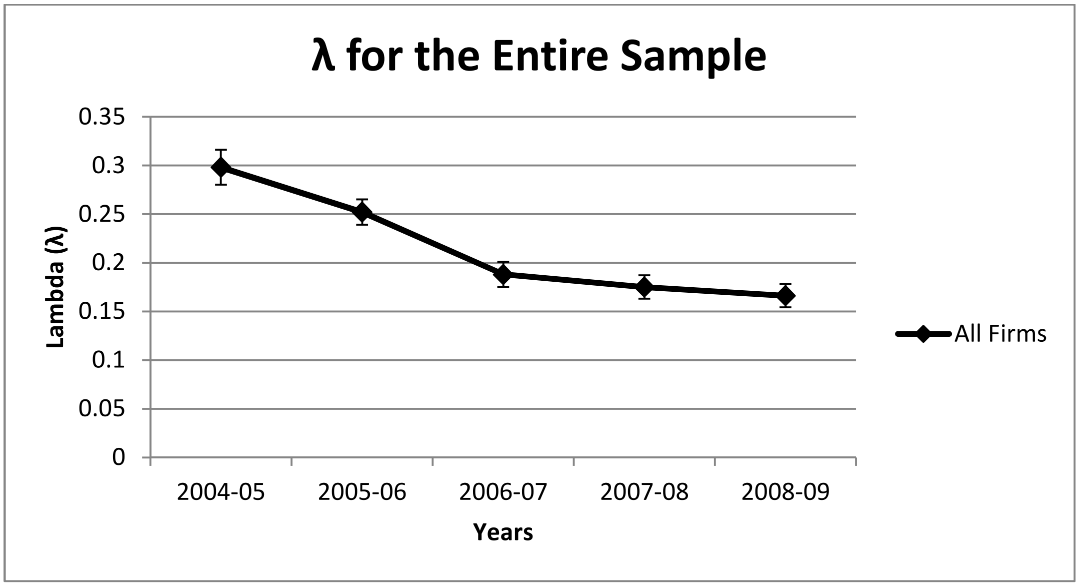


Figure B2: Speed of Learning for the Surviving Firms

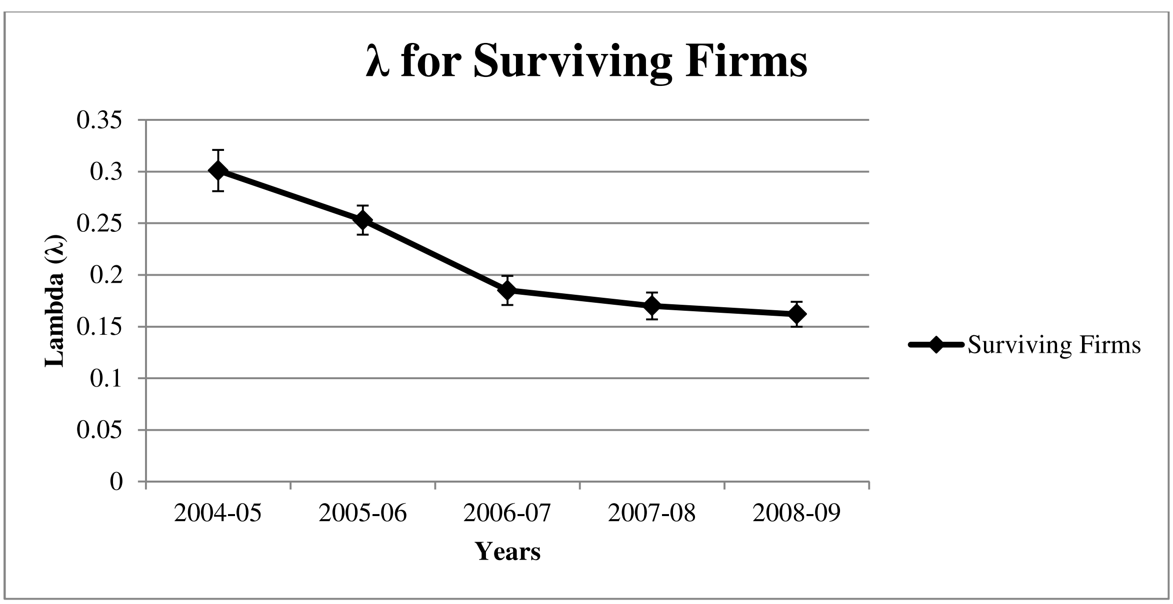
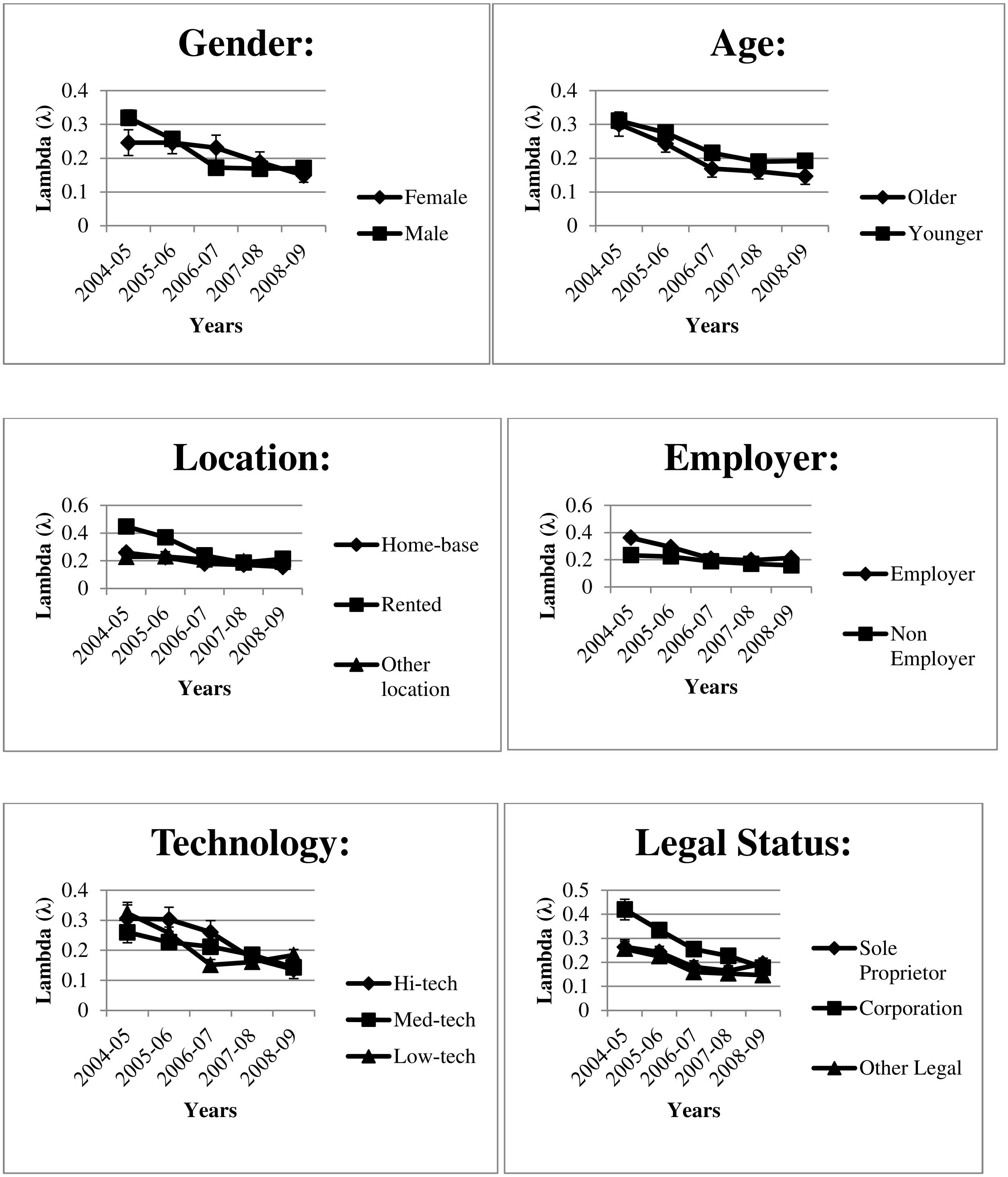


Figure B3: Comparison Based on Groups:



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