Cutting your teeth: the beginning of the learning curve

Cutting Your Teeth: The Beginning of the Learning Curve

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Abstract--We explore learning-by-doing in an important setting not previously explored- the context of one or more complex experiences encountered in novel circumstances. We explore characteristics that lead to learning at the beginning of the learning curve. We use data from survey responses of 2,111 entrepreneurs to examine performance of startup firms as a measure of outcomes produced by learning-by-doing from prior founding experience. Results indicate substantial productivity benefits accruing from prior entrepreneurial experience. We are the first to exploit panel data on the entire individual history of firm founding to control for individual fixed effects. Areas where entrepreneurs show possible learning effects include the inclination and/or ability to more quickly go through the process of recognizing an opportunity, developing it, and executing the exit strategy.

I. INTRODUCTION

Economists as early as Arrow [1] examined the idea that economic growth is fueled by technical change that itself is driven by learning from the activity of production. Although Arrow notes that learning associated with "*repetition of essentially the same problem is subject to sharply diminishing returns*," few in the decades since have examined the very beginning of the learning curve where the problems are more heterogeneous and learning is (purportedly) at its most productive. Our subject here is the beginning of the learning curve where samples of experience are small and learning is challenging, yet potentially highly rewarding [2].

Schumpeter [3] envisioned entrepreneurship (a wave of creative destruction, in his words) as the efficiency inducing engine of the capitalist system. However, if the view is correct that long run economic growth is sustained by a process of learning-by-doing (which drives technical change), then it is worthwhile to ask whether the entrepreneurial process itself is subject to learning.[1] If there are diminishing returns to learning-by-doing, then an understanding of differences in learning rates at the beginning of the curve may be especially important. The relative lack of empirical studies of learning-by-doing in the context of founding new firms is surprising given the implications drawn from learning curve studies for competitive strategy and "first-mover" advantages [4, 5]. The contribution of this article is in studying the beginning of the learning curve and in examining the transfer of learning by founders to subsequent firms, a novel mechanism of learning spillovers across firms.

[1] Beyond examining learning-by-doing in an important, novel setting, a better understanding of the beginning of the learning curve is particularly important for understanding variation in learning rates as well as external spillovers.

II. BACKGROUND

There is a large literature on learning-by-doing including Spence [4], Fudenberg and Tirole [6], Jovanovic and Lach [7], Rosen [8] and Cabral and Riordan [9] among many others. Increases in productivity with cumulative production experience have been demonstrated in numerous manufacturing settings from airplanes to semiconductors where activity is highly repetitive [10-13]. Decreases in unit costs with a doubling of cumulative experience are estimated to range from 55% to 100% [14]. It is controversial whether learning-by-doing should be found in more complex strategic contexts such as new firm foundings or acquisitions. Thus far, the literature on learning-by-doing examines contexts which are seemingly quite far from entrepreneurship. Much of the theoretical work examines monopoly or oligopoly settings using models of learning in firms competing in prices or in finding an innovation [9]. Increasingly, work on learning-by-doing appears to be moving towards examining strategic choices and performance outcomes in competitive contexts where firms are price-takers.

Beyond documenting learning-by-doing, other work has examined the effects of learning on competitive outcomes [15]. Spence [4] examines implications of learning for performance by analyzing competitive interaction in an industry with unit costs declining with cumulative output.[2] Empirical work on the chemical industry has shown that learning effects are greater in magnitude than economies of scale [16]. Balasubramanian and Lieberman [17] show that industry learning rates are connected to firm performance and higher rates of learning are associated with wider dispersion of profitability and Tobin's *q*. The learning curve slope has been found to have a high degree of variance across organizations [18, 19].

If learning has an impact on competitive outcomes, then the question arises about the specific mechanisms of this effect. Closer to the context of interest to the current work, learning has been used to model R&D races, learning curve spillovers and other more strategic types of behavior [6, 20, 21]. Moving away from examining monopoly or oligopoly, more recent work examines more competitive market structures with free entry, exit and price taking firms.[3]

[2] Implications of learning curve models have been derived for production decisions, firm dynamics, and firm valuations [73-77].

[3] Petrakis and coauthors [78] find that mature firms earn rents on their learning despite the fact that equilibrium profits are zero. Zimmerman [79] looks at the commercialization of new energy technologies and finds that learning externalities were present, but only had a small impact on the rate of commercialization. Equilibrium models have shown that learning by doing can endogenize the selection of new goods for production [80]. Other studies have shown that market experience can eliminate anomalies to

Despite much theoretical work, little empirical work on competitive outcomes such as concentration and industry structure has found strong impacts of learning-by-doing. If there are large spillovers to learning then a weak connection between learning-by-doing and competitive outcomes might be expected.

Finally, another stream of literature has examined the extent to which learning-by-doing may spillover outside of the firm [22-24]. Most of the literature treats knowledge as a kind of firm-specific good [25], but there can also be task-specific rather than firm specific human capital which may then be transferred outside of the firm [26] as well as internally [13]. Empirical work outside of economics has begun to explore learning from rare events with intriguing, yet contradictory, mixed results [27, 28]. Zollo and Singh [28] find that, in the context of mergers, experience accumulation is non-significant. Baum and Dahlin (2007) find evidence consistent with learning from train crashes. Some have suggested that learning rates may be higher in slightly heterogeneous settings [29, 30]. Other authors have emphasized the undersampling of failure [27], or how the distribution of resources can limit learning from unusual events [31].

Learning in Entrepreneurial Settings

Employees gain some of the benefits of learning-by-doing and then may leave to start firms based on know-how from their employers [32]. In terms of the entrepreneurial process itself the founders clearly were in a position to learn the most. The original founders of the firm may leave, having learned either something about the process of founding a firm, or about their own ability or efficiency which then affects strategic choices in the subsequent firm [33]. The current article makes its contribution in examining a different knowledge spillover mechanism: whether entrepreneurs appear to transfer some type of learning as a result of the prior founding experience to a subsequent founding. The challenge for such entrepreneurs is that unlike manufacturing settings with large samples of very homogenous production experience, the setting of founding a firm is both infrequently encountered and more heterogeneous in nature. Both characteristics are common to the beginning of a learning curve. If learning-by-doing can be found in the context of entrepreneurs, then this has important implications both for the training of future entrepreneurs and potential policy implications in encouraging serial entrepreneurship or early first founding attempts.

The entrepreneurship literature is beginning to focus on the process of learning among entrepreneurs. Politis [34] has an extensive review and synthesis of the research on entrepreneurial learning. Analyses of the impact on performance of founding experience have varied, with some showing no effect [35, 36] whereas others show performance advantages for multiple entrepreneurs [37, 38].[4] Although they argue against a learning interpretation, the work most closely related to this article is that by Gompers, Kovner, Lerner, and Scharfstein [39]. The authors argue that a large component of success in entrepreneurship and venture capital can be attributed to skill rather than luck and show that entrepreneurs with a track record of success are more likely to succeed than first time entrepreneurs. However, the Gompers et al. sample is limited to founders who received venture capital financing, thus the authors lack data on the much larger proportion of prior foundings that were not VC funded. Furthermore, many more successful start-ups undergo acquisition rather than IPO as opportunities to go public vary with the economic environment and by industry. Therefore the Gompers et al. analysis may be missing many actual prior successes which would tend to bias their estimates. If, and to what extent, small samples of experience result in learning that can be applied successfully in later comparable situations remains to be established.

Definitions

In discussing rare experiences, we want to be explicit in defining both of those terms. First is the term “rare”. Prior work has not defined precisely the line between inference from small samples learning and that of large samples. We follow the spirit of Zollo and Singh [28] that infrequent events are notoriously more difficult to learn from than more repetitious events typically found in learning curve studies. We extend March and colleagues’ [40] definition of samples of one or fewer up to samples of n = 10 where each is infrequent. Experience in founding two, three, or even four firms is still rare experience because each founding experience uniquely occurs in a different business environment, and encounters new problems that are dealt with by the founders. Although learning occurs “on the job”, much of the entrepreneur’s learning may also happen between ventures when outcomes are realized and the entrepreneur has time to reflect on what has happened, what worked, and what was a mistake. Thus, even if the amount of experience in the population is small, “rare experience” should not be a relative concept (i.e. only two experiences to infer lessons from should still count as “rare” regardless of the average number of experiences in the comparison set).

Second is the term “experience”. Experience can mean many things and all of them may be relevant or legitimate, but in this article, we are specifically concerned with experience in starting a business. Experience in starting a business varies to some extent depending on the industry, location, type of business, the growth intentions of the founders, and many other dimensions. However, a common set of experiences occur in forming and developing a new

irrationality such as the endowment effect [81] and that not only learning is important, but also organizational forgetting [82].

[4] Shane [83] has examined the impact of prior experience on opportunity recognition. Our focus is on differences between entrepreneurs who have heterogeneous levels of prior founding experience. Although we cannot directly measure the experience of the founders in recognizing opportunities, what we have in mind is more on the overall execution of founding a firm.

business idea, finding and recruiting co-founders and initial employees, fundraising, and assembling the resources necessary to start a new firm. This set is fairly common across businesses. We focus upon a specific type of experience, namely, experience in doing the set of activities that are required in founding and setting up a new business.

The appropriate unit of prior experience is not immediately clear, but we believe that if task repetition is the basis for learning, then the number of firms started is the appropriate unit of measurement. If the majority of learning relevant to founding occurs in work experience or life experience outside of prior foundings, then we should find that the number of prior firms lacks explanatory power. Because firms develop at different paces in different industries and the wisdom of early decisions is often not known until the founders have experienced some sort of exit event (if ever), we propose that the number of new ventures, rather than years with a single venture, is a more suitable proxy for the amount of prior experience.[5] Another problem with using the number of years of experience is that it implicitly penalizes an entrepreneur who quickly took a firm successfully to acquisition or IPO. Similarly, with focus on the repetitive task, pilots might be expected to learn from the number of flights or take-offs and landings, not from the number of miles flown. Firemen should be expected to learn from the number of fires put out and police officers from the number of arrests made, not the amount of time on a particular fire or with a particular suspect. Entrepreneurs cannot truly gauge the ultimate success of their actions until the final outcome is known.

The key theoretical claim of interest for the current article is that prior startup experiences lead to higher performance in subsequent ventures due to learning from these rare experiences despite the small sample from which to make inferences. As learning represents an interaction between individuals learning and their organizational context, we formulate a series of hypotheses concerning (1) that learning occurs, and (2) characteristics of the organizational context which may influence the degree of learning. We use the model of learning-by-doing of Jovanovic and Nyarko [41] to relate learning-by-doing to firm performance. The model is an information-theoretic model that describes information gained from prior experience as an input into the current efficiency level. It is described in greater technical detail in their article and its advantages in this setting along with the setup and results are summarized in Appendix B.

Although higher performance in subsequent ventures would be consistent with a number of mechanisms in addition to learning, as a first pass if performance is not higher with founding experience then a learning interpretation should be questioned. Organizational performance in entrepreneurial firms is likely to be a noisy proxy for learning. Nonetheless, because the prior entrepreneurial experience of the founders is a major input for a new venture, organizational performance is a relevant and appropriate objective measure. Performance can be seen as a very conservative test for learning. For it to be detected, learning must occur at a high enough level to impact performance in a large sample of organizations. As most studies of learning are within organizations, it may well be controversial to suggest that learning which took place within or based upon experiences with one firm will readily transfer to a new organization and with sufficient power to improve organizational performance [42]. Nonetheless, we believe that the knowledge gained via a founding experience is valuable enough that even in the dynamic, turbulent environments characteristic of new firms [43] performance improvements should appear.

> ***Hypothesis 1a: Individuals will exhibit performance improvements as a result of learning from prior founding experiences.***

An alternative explanation for why performance might appear to improve with prior founding experience is that those who choose to start a second firm have higher skill levels than those who choose to only start a single firm [39]. If those who start multiple firms are also more persistent or more talented than those who start only one firm, then we would also observe average performance improvements as lower skill individuals exit from entrepreneurship. We exploit the panel structure of the data, which includes observations of multiple firm foundings for many individuals to implement a regression including individual fixed effects to control for time-invariant factors from the individual influencing performance.[6] Also, conditioning on one firm founding, the results should not show performance improvements with prior founding experience if underlying skill or persistence is the only component. In addition, conditioning on at least one prior firm founding addresses the problem that some of the entrepreneurs with a single founding may be lifestyle entrepreneurs who are starting a firm with no intentions to grow or sell it. If there is some form of learning in addition to differential skill levels, then conditioning on high persistence (more than one firm founding) we expect to continue to observe performance improvements with prior foundings.

> ***Hypothesis 1b: Conditioning on individuals with at least one prior founding experience or controlling for individual effects, organizational performance will improve with the number of prior founding experiences.***

[5] Years of experience is not a good measure here because for example, an individual may be moonlighting and working part time in another job making the number of 'years' experience a messy measure. Our analyses were also run with the number of years of prior startup experience but this variable was not significant.

[6] These may include individual-level factors such as ability or persistence which without individual fixed effects would exert an upward bias on estimates of learning-by-doing and also factors such as a preference for variety or for multiple "lifestyle" businesses or the inability to hold down wage employment which would exert a downward bias in studies lacking observations on multiple firm foundings.

Various mechanisms have been proposed for the variation between organizations in learning rates [44]. Our second set of hypotheses focuses on characteristics of the prior experience. Whether the event turns out as a success may influence what knowledge the individual takes away from a previous experience and how she or he applies that knowledge to future situations [45]. Starbuck and Hedberg [46] review the cognitive and behavioral research on how success impacts learning, and identify a number of interesting mechanisms at work. Yet, their review shows the difficulty in formulating compelling arguments for success/failure having a straightforward impact on levels of learning. Entrepreneurs evaluate their performance much differently than researchers do [47], and when links between actions and outcomes are ambiguous, sensitivity to levels of performance may decrease [48]. Politis [34] argues that prior experiences of success or failure may condition the mode of learning from experience. Prior success can show a path forward, but it may not spur much additional thought about why the success occurred. McGrath and Gunther [49] emphasize that failure can have positive benefits by increasing the search for new opportunities. Failure can create greater variety in actions as the individual searches for strategies to reduce uncertainty [50]. However, we simplify the arguments by noting that in this context, prior experiences that were more successful allow the entrepreneur to experience more of the startup process, rather than having it end early; they show the entire path to success, rather than just part of it. In the context of the model, more successful prior experiences provide signals for a larger proportion of the *N* tasks and low initial disturbances result in a faster learning rate.

Hypothesis 2a: Individuals who have experienced success (as evidenced by prior IPOs or acquisitions) will exhibit higher performance improvements from prior founding experiences.

In psychology, a transfer effect is the beneficial impact of a prior event on the performance of a subsequent event [51]. The similarity between the characteristics of events influences the probability of positive outcomes from transfer [52]. The probability of negative outcomes can increase when events are dissimilar yet lessons from prior experience are applied anyway [51]. We suggest that transfer effects occur between the individual and the organizational levels of analysis. An individual can bring transfer effects, perhaps in the form of routines from prior founding experience to the benefit (or detriment) of a new organization's performance, depending on the similarity of industrial contexts [53, 54]. As Gavetti et al. [55] indicate, the problem with forming strategy by analogy is that it requires both a breadth of prior experience to draw from (which may not be available) and a good fit between the relevant dimensions of the current, novel situation and the prior situation. A certain level of learning must have already taken place. Inferences may be misapplied or the wrong inferences from the beginning [51]. Indeed, Henderson and Clark [56] argue that if the environment is characterized by demands for architectural innovations in the firm, which do not match the architecture of the manager's prior organization, learning by analogy may prove difficult. According to the Jovanovic and Nyarko [41] model, this type of situation would result in greater uncertainty as to the optimal values and thus a flatter learning curve. Furthermore, examining the impact of the similarity of experience will allow us an additional test of whether higher performance for subsequent firms is a learning effect or a result of higher skill for serial entrepreneurs. Unless higher skill founders tend to remain in the same industrial context, better performance for those with experience in a similar industry compared to those with prior experience in a different industry should be a sign of learning as the correct mechanism.

Hypothesis 2b: Individuals who remain in similar contexts (as evidenced by industry SIC code) will exhibit higher performance improvements from prior founding experiences.

III. METHODS

A. Data and Sample

We analyze data from a novel survey administered in 2003 to all MIT alumni who had previously self-identified as founding at least one new venture. Out of 8,242 alumni who had indicated that they had founded a company, 2,111 founders completed surveys, representing a response rate of 25.6%.[7] Examining the firm names and founding years, we identified and dropped 44 duplicate observations where multiple cofounders reported on the same firm. Industries covered include aerospace, architecture, biomedical, chemicals, consumer products, consulting, electronics, energy, finance, law, machine tools, publishing, software, telecommunications, other services, as well as other manufacturing. A total of 3,156 alumni indicated that they had started multiple companies, of whom 960 completed the survey for a multi-founder response rate of 30.4%.[8] A total of 1,107 single-firm founders responded to the survey giving a 21.8% response rate out of the 5,086 single-firm alumni founders. Some of these 1,107 single-firm founders may later become multiple entrepreneurs, however as we are looking at the learning effects of prior founding experience on current firm performance, this is not a problem for our current research. The founders reported information on up to five firms which they had founded across their careers yielding a total of 3,698 firm observations. There is an average of 1.79 firms founded per individual or 3.85 firms per individual who founded more than 1 firm. The founders were also asked for the total number of firms they had attempted to found over the course of their career and 80

[7] Appendix A shows *t*-tests of the null hypothesis that the average (observed) characteristics of the responders and non-responders are the same statistically, for both the 2001 and 2003 surveys.

[8] To be clear, the vast majority of these individuals were 'serial' entrepreneurs. They have left the first firm before founding a subsequent firm rather than owning multiple businesses at the same time.

indicated having founded more than 5 firms (up to 11). The average number of firms per individual by this measure is 2.13 so we appear to have captured data on the vast majority of firm foundings. To provide still more information about these companies including current sales, employment, industry category and location, this new MIT database was further updated from the records of Compustat (for public companies) and Dun & Bradstreet (private companies).[9] For consistency in the country and institutional context, the 1,121 firms which were identified as having been founded outside of the U.S. were dropped from the analysis. Information on sales was adjusted for inflation to constant dollars.

Determining the appropriate level of analysis is a problem when thinking about learning from small samples. Although teams of multiple co-founders are more likely to start a new firm, as well as be more successful in their firms [47], we only have complete founder information on prior startup experience for one entrepreneur from each team. Previous findings of strong homophily among founding teams indicate that the prior founding experience of one entrepreneur may be a good proxy for that of the team [57] and the results are robust to using only the single-founder teams and to using all co-founded teams. To eliminate concerns of biases in the Dun & Bradstreet data, the analyses are also run on only the subset of firms for which the founders provided more detailed revenues and employee data (each founder chose one firm to provide more detailed data). Although we lose the panel structure, this sub-sample also provides us with more detailed information on control variables and increases the confidence in our results. Due to skipped survey items and missing data we limit our primary performance analyses on revenues to the 964 firms (single founder and co-founded teams) for which we have complete data. For our analysis on lags between firm foundings, we have complete data on a sample of 587 firms. Meaningful numbers of foundings begin in the 1950s, therefore we restrict our analysis to firms founded from 1950-2001. A key feature of this dataset is its long time horizon allowing us to analyze entire entrepreneurial careers.

B. Measures

Dependent Variables. Because our focus is on measuring the performance effects of learning, we use revenues, acquisition, IPO, employees, and lag between foundings as the dependent variables. Profit might be a better indicator, but we lack adequate profit data to use that measure. The pair-wise correlation between employee size and log revenues was -0.024, so we do not believe revenue is picking up only size effects. No single outcome measure is ideal. Using acquisitions has the drawback of not observing the valuation of the acquisition as compared to the valuation at the time of funding. Similarly, using IPOs does not identify the valuation of the firm at the time of the IPO, or the post-IPO performance of the stock, or the personal financial benefits to the founders or the initial investors. Both IPOs and acquisitions apply only to a subset of foundings, not to all of them, whereas revenues are a common goal of all companies. Many studies of entrepreneurship use the fact of an IPO as a measure of success [39, 58]. But far more startups successfully exit via acquisitions than via IPOs. It is important to recognize that performance, particularly for entrepreneurial firms, is multidimensional in nature [59]. The limitation of using the fact of IPO or acquisition is that both of these are sensitive to the industry, the economic environment, and the founders' desire to retain control. It is best to consider multiple performance measures, which is why we look for (and find) robustness with various measures. The variable *LOG REVENUES* is the revenue for the most recent fiscal year in operation as reported by the entrepreneur. We adjust for inflation (2001 $) and take the natural log of this measure for our dependent variable.[10] Out of 2,111 firms, 1,370 survey respondents reported revenues for their firms ranging from $0 to $2.56 billion (mean = $34.6 million, median = $1.12 million). *LAG FROM FOUNDING TO FOUNDING* is the number of years from founding one firm to founding the next firm. We use acquisition in event-history models as well.

To alleviate concerns of response bias where defunct firms might be non-responders, we examine the proportions of firms "in operation", "acquired", and "out of operation" in the group reporting revenues (1424 observations) and the group of non-responders (687 observations) to this question. Our concerns are alleviated in finding that the proportions are roughly equivalent with 68.5% of those reporting revenues still in operation and 62.3% of the non-responders still in operation. 10.9% of the reporting firms were out of operation whereas that number is 18.8% for the non-responders. 19.7% of the reporting firms had been acquired subsequently, whereas 18.8% of the non-responders had been acquired.

Independent Variables. We use independent variables related to the characteristics of the founding team and the nature of the prior experience, as well as a number of controls. The key independent variable is *NUMBER OF START-UPS FOUNDED*, which is coded as the ranking of the current firm in terms of whether it is the first firm, second, third, and so on (mean = 1.61), founded by a given entrepreneur. For an entrepreneur on her second firm, this variable would be coded as a 2. Because each observation is a single entrepreneur and the total number of his prior firms, the observations can be considered independent. This variable represents a widely used measure of the amount of startup experience from which the entrepreneur has had an opportunity to learn [34, 60]. *PRIOR IPOS* is the number of previous IPOs for an entrepreneur's previous firms. The variable *PRIOR ACQUISITIONS* is a count of the number of a founder's prior

[9] Successful matches were found for 80% of the company names in the D&B database. A firm is included in the Dun and Bradstreet database when it needs to obtain a credit rating. An analysis of Dun and Bradstreet's coverage compared to other sampling sources for small businesses concluded that there was not a bias towards larger firms [84].

[10] Adjusting for inflation is not entirely necessary since year dummies are used; however they were already calculated for use in descriptive statistics.

firms which have been acquired. Although survival is often used as a performance measure, survival exists among underperforming firms [37]. Capturing the similarity of the industrial context, *SAME 2-DIGIT SIC CODE* is a count of the number of prior startups that have the same 2-digit SIC code as the current firm. *DIFFERENT 2-DIGIT SIC CODE* is a count of the number of prior startups with a different 2-digit SIC code as the current firm. SIC and VEIC codes were matched from the Dun & Bradstreet Million Dollar database and from VentureXpert. VEIC codes were converted to SIC codes with a previously used matching scheme [61].

Control Variables. A set of *INDUSTRY DUMMIES* controls for the coarse industry segment within which the firm competes (such as biotech, software, and electronics). The variable *AGE AT FOUNDING* is the entrepreneur's age when the firm was founded. Individuals also differ in their starting human capital and in particular in the number of years of education they have received. Previous work has also shown a link between education as human capital and the performance of entrepreneurial firms [62-65].[11] We control for *BACHELOR'S DEGREE* and *MASTER'S DEGREE*. We control for the age of the startup, as measured by *OPERATING YEARS* from founding to the year for which revenues are reported. A set of *YEAR DUMMIES*, one for each year from 1950-2001, captures temporal changes in the economy. *INITIAL CAPITAL* is the natural log of the amount of initial capital raised (adjusted to 2001 dollars, roughly defined as capital raised within the first year after founding).[12] One alternative explanation to learning for which we attempt to control is the possibility that entrepreneurs are simply gaining a larger social network as they found successive firms. The same results held when we constructed the sample to include only sole founders (not founding teams) eliminating one potential avenue through which a larger social network could improve subsequent firm performance. Entrepreneurs starting a firm in the same geographical location where they started a firm previously are likely to enjoy greater networking benefits. Prior work has shown that most communication is with those in closer physical proximity [66]. Thus, whether through greater contacts with the local financial industry, more peers for discussing entrepreneurial ideas, or greater connections to high quality first employees, entrepreneurs remaining in the same location should enjoy greater benefits from prior experience in the form of larger social networks as well as learning the startup process. Therefore, testing the impact of prior learning experience from startups formed in the same location as compared to those formed in a different location should allow us to a certain extent to disentangle this social capital effect from the increase in human capital. *NUMBER SAME STATE* is the number of prior startups by the entrepreneur in the same U.S. state as the current startup. *NUMBER DIFFERENT STATE* is the number of prior startups in a different U.S. state from the current startup. If the benefit from prior experience disappears for foundings in different locations then this supports the idea that we are observing primarily a social network effect (or that there are performance-influencing differences in the characteristics of those entrepreneurs who change locations).

TABLE 1. DESCRIPTIVE STATISTICS

Variable	Obs.	Mean	Std. Dev.	Min	Max
LOG REVENUES	1264	14.05	3.08	0.03	21.66
ACQUIRED	1840	0.19	0.39	0	1
IPO	1790	0.11	0.32	0	1
LAG BETWEEN	1502	12.11	9.41	0	50
NUMBER OF FIRMS	2058	1.61	1.30	1	11
PRIOR ACQUISITIONS	2067	0.13	0.42	0	3
PRIOR IPOS	2067	0.04	0.23	0	3
PRIOR SAME SIC	1473	0.02	0.14	0	2
PRIOR DIFFERENT SIC	1473	0.02	0.18	0	3
PRIOR FOUNDINGS IN THE SAME STATE	2067	0.38	0.90	0	8
PRIOR FOUNDINGS IN A DIFFERENT STATE	2067	0.23	0.79	0	7
AGE FOUNDED	1807	39.65	10.59	18	83
AGE FOUNDED SQUARED	1807	1684.19	920.07	324	6889
BACHELOR'S DEGREE	2000	0.43	0.49	0	1
MASTER'S DEGREE	2000	0.41	0.49	0	1
OPERATING YEARS	1837	14.34	11.30	0	74
INDUSTRY	1600	9.77	4.34	1	16
NUMBER OF COFOUNDERS	2056	1.05	1.22	0	4
VC FUNDED	1691	0.13	0.34	0	1
LOG INITIAL CAPITAL	1264	11.91	2.72	0.28	21.02

[11] Macroeconomists also have a long tradition of examining the impact of education on growth [85]. Recent reviews of the literature on education and entrepreneurship and on the returns to education more generally have been compiled by others [86, 87]. Murphy et al. [65] acknowledge that the direction of causality may be reversed here, however: countries with faster growth may provide more engineering jobs and may support more engineering education. Roberts [47] shows a curvilinear relationship between education level of high-tech entrepreneurs and their firms' overall performance, with Master's degree recipients doing best. An alternative is the signaling argument where an advanced degree signals the individual as a 'high type' who is a quicker learner with lower costs of educational attainment [88].

[12] There is some uncertainty around the way that respondents interpreted the time frame and some may have waited for a funding event to found the firm. Although the measure is admittedly not ideal, it is the best proxy available, particularly for non-venture capital backed private firms.

Descriptive statistics are presented in Table 1. The number of observations varies due to missing observations on the survey items. Table 2 shows median inflation-adjusted revenues and Panel B shows the lag between founding firms. The trend from a median of $836,000 for first firms to $7.27 million for 5th (or more) firms lends support to Hypothesis 1a that something is making subsequent firms more successful. The table also reassures us that we are not simply capturing differences between any prior experience and no prior experience. Table 2 shows the standard deviation in the revenues decreases across subsequent firms indicating that founders may be growing risk averse or undertaking less ambitious ventures. Although Table 2 suggests a decrease in the lag between firms across subsequent ventures, the differences are not statistically significant.

TABLE 2. REVENUES AND LAG ACROSS VENTURES

Panel A – Likelihood of Exit Events and Revenues (in 2001 dollars)					
Firm Rank	**1st firms (N=556)**	**2nd firms (N=182)**	**3rd firms (N=84)**	**4th firms (N=21)**	**5th firms and higher (N=36)**
Median Revenues ('000's)	836	1,784	924	1,181	7,274
Standard Dev. ('000's)	153,000	117,000	130,000	10,800	21,200
Panel B – Lag (from graduation and from the prior firm founding)					
Firm Rank	**1st firms (N=761)**	**2nd firms (N=241)**	**3rd firms (N=150)**	**4th firms (N=71)**	**5th firms and higher (N=31)**
Lag Between Subsequent Firms (years)	14.02	7.95	7.38	6.99	6.71
Lag St. Dev.	9.78	6.90	6.73	5.42	6.37

IV. RESULTS

A. Multivariate Regressions on Firm Performance

These descriptive results are suggestive of learning effects. To more systematically test the hypotheses, we use multivariate regressions beginning with a baseline model followed by results controlling for factors that may be confounding the results including: 1) individual fixed effects and 2) specific firm characteristics, social networks, and fundraising. We then further reinforce the results by testing whether learning effects may speed the timing of events.

Baseline regressions

The traditional approach to measuring learning-by-doing for a product is to estimate a power-law function of the following form:

$$C=\alpha X^{-\beta} \quad (1)$$

Where C is the unit cost of the product, α is a constant, X is a measure of experience (prior cumulative production in traditional cases and β>0 is the rate of learning-by-doing. However, this approach is not possible in our case because it requires detailed cost data that are not easily available for private entrepreneurial firms. Our method for measuring learning-by-doing incorporates learning-by-doing within a variant of a production function modified to better fit the case of entrepreneurial firms. Traditionally we would write an equation of the form:

$$Y=F(K, L, X) \quad (2)$$

Where Y is the current period performance, K and L are capital stock and quantity of labor, respectively, and X is a measure of experience. The Cobb-Douglas production function is widely used, but in the case of entrepreneurial firms, output and capital in particular are extremely difficult to measure for a number of reasons.[13] Prior experience of the founders is considered an "input" into the start-up process in the sense that a higher level of prior experience increases performance (controlling for the level of labor and capital). The coefficient on prior experience denotes the learning intensity. First we use the baseline multivariate regressions shown in Table 3. The specification of the regression model is as follows:

$$yit = \Phi(\beta' x\ it) \quad (3)$$

where y_{it} is a measure of firm performance, and the vector x_{it} includes our demographic and firm level variables including the number of prior firms. Subscripts indicate a founding year and 2-digit SIC code. Individual fixed effects are not included in this baseline set of models. Each column uses a different performance measure as the dependent variable including revenues (3-1), acquisition (3-2), initial public offering (3-3), employees (3-4), and years of survival (3-5).

[13] For a start-up firm, having raised external capital at all has been viewed by prior literature as a signal of performance and thus can be criticized as endogenous to the start-up performance that we are interested in measuring.

TABLE 3. PRODUCTIVITY REGRESSIONS

Independent Variables	LN(REVENUES) (3-1)		PR(ACQUIRED) (3-2)		PR(IPO) (3-3)		LN(EMPL) (3-4)		LN(SURVIVAL) (3-5)	
NUM. OF START-UPS FOUNDED	-0.269	(0.206)	0.040	(0.051)	0.002	(0.069)	0.066	(0.057)	-0.028*	(0.016)
NUM. PRIOR ACQUIRED	0.121	(0.328)	0.396***	(0.087)	0.084	(0.116)	0.160	(0.103)	0.058	(0.024)
NUM. SAME 2 DIGIT SIC	0.396	(0.456)	-0.239*	(0.125)	-0.014	(0.161)	0.442***	(0.143)	0.014	(0.034)
AGE AT FOUNDING YEAR	0.025	(0.013)	-0.012***	(0.004)	0.001	(0.005)	-0.012***	(0.004)	0.006	(0.001)
GENDER (1=MALE)	1.179***	(0.648)	0.404**	(0.202)	0.372	(0.289)	0.582***	(0.153)	0.059	(0.052)
MASTERS	-0.237***	(0.287)	-0.016	(0.076)	0.170*	(0.103)	0.305***	(0.086)	0.040	(0.028)
DOCTORATE	-0.183*	(0.409)	-0.192*	(0.102)	0.117	(0.130)	0.181	(0.121)	0.111	(0.036)
LN(EMP)	1.752	(0.292)	0.055***	(0.019)	0.188***	(0.025)				
LN(FIRM AGE)	0.539	(0.076)	0.173***	(0.057)	0.358***	(0.097)	0.532***	(0.074)		
MA	-0.546*	(0.332)	0.330***	(0.081)	0.260***	(0.104)	0.214**	(0.098)	-0.021	(0.030)
CA	-0.177	(0.346)	0.389***	(0.092)	0.440***	(0.123)	-0.030	(0.102)	0.010	(0.033)
CONSTANT	-13.826	(3.467)	-1.422	(1.347)	-2.543***	(0.994)	-3.290***	(0.626)	1.412***	(0.198)
Year F.E.	YES		YES		YES		YES		YES	
SIC F.E.	YES		YES		YES		YES		YES	
Individual F.E.	NO		NO		NO		NO		NO	
R-squared	0.2164		0.160		0.228		0.150		0.622	
Num. of obs.	1294		1997		1760		2092		2217	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

In Model 3-1, the prior founding experience variables are not significantly associated with higher revenues. The number of employees and firm age are included as controls, so this is an analysis of firm productivity. Model 3-2 shows that the number of prior start-ups which were acquired is positively and significantly related to the likelihood that the current firm is acquired. However, starting a new firm in the same 2-digit SIC code is negatively associated with the likelihood of acquisition. Having a male founder, greater numbers of employees, older firms, and being located in Massachusetts or California is also correlated with higher likelihood for an acquisition. In Model 3-3, none of the key independent variables are associated with the likelihood of an IPO. Looking at the number of employees as the dependent variable, Model 3-4 shows that the number of prior firms in the same industry is associated with a larger firm size. Finally, Model 3-5 shows that with more prior founding experience, entrepreneurs appear to close subsequent firms more quickly. This is consistent with increasing opportunity costs of running an underperforming firm with higher levels of start-up experience.

Controls for Individual Effects

Although intriguing, these results are not conclusive, mainly due to the lack of controls for individual level differences which may be correlated both with the likelihood of founding additional firms and with performance. The results in Table 4 drop the unchanging individual characteristics for education, location, and gender and instead exploit the multiple observations on individuals to include individual fixed effects which capture time-invariant differences in individuals which may include higher underlying skill, persistence, family wealth, or preferences for variety which are likely confounding the earlier estimates. Again, Model 4-1 finds that the prior start-up experience is not associated with higher revenues. Model 4-2 shows that once individual fixed effects are included, higher levels of start-up experience are strongly associated with a higher likelihood for acquisition. However, the coefficient on the number of prior start-ups which were acquired is strongly negative and significant, indicating that having a prior start-up decreases the likelihood that the current firm will be acquired (perhaps because these founders have either started lifestyle businesses or they are aiming for an IPO). In Model 4-3, the number of prior acquisitions is statistically significant and shows a higher likelihood of an initial public offering for the current firm. None of the prior experience measures in Model 4-4 are associated with a greater number of employees. Model 4-5 looks at survival and finds that whereas those with more prior foundings survive longer, those with more prior firms that were acquired have lower survival. Again this is consistent with a story that prior experience improves survival with a moderating effect of prior success which raises opportunity costs and causes individuals to be quicker in shutting down bad firms. For three out of the five performance and productivity measures, some measure of prior founding experience is associated with better outcomes.

Controls for Detailed Firm Characteristics

The analysis thus far is supportive of the idea that there is a learning effect from the experience of founding a firm. However, using the panel data we lack information on certain control variables which may be important such as the amount of capital raised, the number of co-founders and whether the firm received venture capital funding. It may be that serial entrepreneurs are better able to raise capital or to attract more co-founders and that this is confounded with learning effects (though they may also be areas where the founder is learning how to improve performance). Controlling for the amount of initial capital also partially alleviates concerns that personal wealth may be driving the results. Survey respondents chose one firm to answer more detailed questions regarding the number of co-founders, initial capital, etc. The following regressions take advantage of these controls and the fact that we know where this firm is located in the ordering of firms founded for each individual (first firm, second, and so on).

TABLE 4. PRODUCTIVITY ANALYSIS INCLUDING INDIVIDUAL FIXED EFFECTS

Independent Variables	LN(REVENUES) (4-1)		PR(ACQUIRED) (4-2)		PR(IPO) (4-3)		LN(EMPLOYEES) (4-4)		LN(SURVIVAL) (4-5)	
NUM. OF START-UPS FOUNDED	0.597	(0.551)	2.326***	(0.181)	-0.099	(0.074)	0.029	(0.129)	0.161***	(0.043)
NUM. PRIOR ACQUIRED	-0.028	(0.747)	-5.105***	(0.221)	0.331***	(0.114)	0.078	(0.186)	-0.119**	(0.060)
NUM. SAME 2 DIGIT SIC	-0.573	(0.799)	-0.298	(0.248)	0.090	(0.154)	-0.034	(0.208)	0.010	(0.064)
AGE AT FOUNDING YEAR	0.363**	(0.160)	-0.103***	(0.010)	0.000	(0.005)	-0.016	(0.011)	0.013	(0.013)
LN(EMP)	1.208***	(0.598)	-0.099**	(0.045)	0.158***	(0.025)				
LN(FIRM AGE)	1.730**	(0.482)	0.359**	(0.157)	0.394***	(0.093)	0.322**	(0.145)		
CONSTANT	-29.591***	(9.765)	-0.126***	(0.066)	-2.105**	(0.959)	-0.643	(1.137)	3.683***	(0.496)
Year F.E.	YES		YES		YES		YES		YES	
SIC F.E.	YES		YES		YES		YES		YES	
Individual F.E.	YES		YES		YES		YES		YES	
R-squared	0.740		0.750		0.206		0.750		0.884	
Num. of obs.	1528		463		1771		2135		2231	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.

TABLE 5. EFFECTS OF PRIOR ENTREPRENEURIAL EXPERIENCE

(Conditioned on having founded at least one prior startup)

Dependent variables	**LN REVENUES**	**PR(ACQUISTION)**	**PR(ACQUISITION)**	**PR(IPO)**
Independent variables	Model 5-1 OLS	Model 5-2 Probit	Model 5-3 Cox Hazard	Model 5-5 Probit
FOUNDER CHAR.				
AGE AT FOUNDING	0.002	-0.001	0.999	0.009
	(0.014)	(0.011)	(0.012)	(0.014)
NUMBER OF COFOUNDERS	0.056	0.024	2.057***	0.192***
	(0.118)	(0.079)	(0.784)	(0.096)
PRIOR EXPER. CHAR.				
PRIOR ACQUISITIONS				
	0.417**	0.389***	1.987*	0.099
PRIOR IPOs	(0.212)	(0.145)	(0.775)	(0.195)
	0.132	0.350	1.003	0.427*
CONTROLS	(0.361)	(0.252)	(0.089)	(0.244)
BACHELOR'S DEGREE				
ONLY	-0.078	0.548*	1.529**	0.046
MASTER'S DEGREE	(0.438)	(0.309)	(0.227)	(0.428)
	0.433	0.478	1.117	0.087
OPERATING YEARS	(0.430)	(0.312)	(0.268)	(0.429)
	0.067*	-0.043*	0.859***	0.048
INITIAL CAPITAL	(0.039)	(0.025)	(0.016)	(0.042)
	0.411***	0.111*	1.209***	0.115*
VC FUNDED	(0.070)	(0.049)	(0.069)	(0.063)
	-0.089	0.519*	1.653*	-0.140
INDUSTRY SEGMENTS	(0.462)	(0.304)	(0.518)	(0.366)
YEAR DUMMIES	YES	YES	YES	YES
CONSTANT	YES	YES	YES	YES
	13.642***	-1.281	--	dropped
Log-likelihood	(3.446)	(1.655)		
χ^2-Statistic (or R-squared)	--	-124.3	-371.78	-78.9
p-value (or Prob>F)	0.432	125.1	138.18	65.9
Number of obs.	0.000	0.000	0.000	0.008
	347	345	439	222

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

To further test these ideas, we condition on having founded at least one prior start-up and run the regressions shown in Table 5. Model 5-1 shows that controlling for founder age, education, the number of cofounders and initial capital raised, and the number of prior firms which went through an acquisition is positively and significantly associated with higher revenues. The same result holds in Model 5-2 for the likelihood of acquisition and in 5-3 when a hazard rate model is used rather than a probit. Model 5-4 uses the fact of IPO as the dependent variable and finds that the number of prior IPOs is related to the likelihood of IPO for the current firm. In addition, teams with more cofounders are more likely to have an IPO. The amount of initial capital is also correlated with performance, though a reasonable interpretation is that the more promising start-ups were able to raise more money during the first year.

B. Cox Hazard and Multivariate Regressions Controlling for Timing

Table 6 begins to explore the idea suggested by the descriptive statistics that experienced entrepreneurs may be able to more quickly go through the start-up process.[14] A

[14] A finding of more quickly executing the start-up process is consistent with either finding a higher quality idea or with learning how to design a company (or to filter ideas) for a more rapid exit.

Cox [67] hazard rate model is used. The specification of the Cox (1972) model is as follows:

$$\lambda(t \mid X) = \lambda_o(t)\exp(X\beta) \qquad (4)$$

where the vector ***X*** includes our founder and first firm experience characteristics. $\lambda(t \mid X)$ is the rate at which firms will be acquired at any particular date, given that they have not been acquired up until that point in time. Equation (3) specifies the hazard rate as the product of two components: a function of the spell length (i.e. delay time since founding the firm), $\lambda_o(t)$ or baseline hazard, and a function of the observable individual and firm characteristics, denoted by the vector ***X***. The model estimates the probability of an acquisition in a given year conditional on not having been acquired up until that time period. This model is appropriate for data like ours where right-side censoring is a problem because the timing of events is taken into account. Subjects start being at risk at the year of founding and the dependent variable is the event of an acquisition. Values above 1.0 represent increases in the hazard of acquisition and values below 1.0 represent decreases. Results indicate that *NUMBER OF PRIOR STARTUPS* (Model 6-1), *PRIOR ACQUISITIONS* (Model 6-2), *PRIOR STARTUPS IN THE SAME 2 DIGIT SIC* (Model 6-4) all significantly increase the likelihood of an acquisition. Both the coefficients on the number of prior foundings in the *SAME STATE* and in a *DIFFERENT STATE* (Model 6-3) increase the likelihood of acquisition and are significant at the 10% level.

TABLE 6. COX HAZARD RATE REGRESSIONS

	Dep. Variable = Acquisition year (subjects start being at risk at year of founding) Note: reported coefficients are hazard ratios			
Independent variables	Model 6-1	Model 6-2	Model 6-3	Model 6-4
Founder char.				
AGE AT FOUNDING	0.989	0.955**	0.969	0.965
	(0.034)	(0.021)	(0.020)	(0.029)
# OF START-UPS FOUNDED	2.224**	--	--	--
	(1.444)			
NUMBER OF COFOUNDERS	1.551	1.563	1.489	1.578
	(0.492)	(0.527)	(0.470)	(0.928)
PRIOR EXPERIENCE CHAR.				
PRIOR ACQUISITIONS	--	2.011***	--	--
		(0.370)		
PRIOR IPOS	--	1.777	--	--
		(0.759)		
SAME STATE	--	--	1.255**	--
			(0.171)	
DIFFERENT STATE	--	--	1.333**	--
			(0.234)	
SAME 2 DIGIT SIC	--	--	--	37.621**
				(56.90)
DIFFERENT 2 DIGIT SIC	--	--	--	3.675
				(3.015)
CONTROLS				
BACHELOR'S DEGREE ONLY				
	0.968	0.959	0.827	0.491
MASTER'S DEGREE	(0.423)	(0.425)	(0.374)	(0.308)
	0.720	0.702	0.673	1.508
OPERATING YEARS	(0.316)	(0.315)	(0.298)	(0.667)
	0.901***	0.884***	0.902***	0.856***
INITIAL CAPITAL	(0.018)	(0.019)	(0.018)	(0.029)
	1.151**	1.116	1.141**	1.209
VC FUNDED	(0.093)	(0.091)	(0.092)	(0.153)
	3.116**	2.988**	3.048**	3.428**
INDUSTRY SEGMENTS	(1.633)	(1.553)	(1.597)	(2.637)
Prob > chi2	YES	YES	YES	YES
LR chi2	0.000	0.000	0.000	0.000
(df)	77.95	88.85	77.85	76.07
	21	22	22	22

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively; hazard ratio and standard errors reported; 374 firms, 53 events and 6,167 obs.

Table 7 uses multivariate regression to test systematically the relative speed of going through the startup process. This model should be interpreted very carefully as due to right-hand censoring we should expect to find decreases in lag as a statistical artifact. Attention should be focused solely upon relative differences in lag length rather than on the fact of a shorter lag. An event history model would have been preferable but was not feasible as we have no information on who is likely to start another firm but has not yet. A reduction in lag could also be due to differences in style. The models use the *LAG FROM FOUNDING TO FOUNDING* as the dependent variable, but the results are also robust to the use of the lag from closing one firm (whether by closing, bankruptcy, acquisition, or IPO) to founding the next one. The specification is that the lag is generated as follows:

$$E[\boldsymbol{y_{it}} \mid \boldsymbol{x}] = \lambda_{it} = \exp(\boldsymbol{\beta}'\boldsymbol{x_{it}}) \tag{5}$$

where $\boldsymbol{y_{it}}$ is a measure of lag, and the vector $\boldsymbol{x_{it}}$ includes our demographic and firm level variables including the number of prior firms. Thus, each of our models predicts the lag between subsequent firms given a founding year and industry category. Because the lag is measured in years and is a count variable that is always positive, we use Poisson-based econometric estimation methods. The expected lag is an exponential function of a vector of the founder's prior founding experience and other characteristics $\boldsymbol{x}$. We note that by construction this analysis limits the sample to those with more than one startup.

TABLE 7. POISSON REGRESSION USING LAG TO NEXT FOUNDING

Dep. Variable	***Lag from founding to founding*** (N=587)			
Independent variables	Model 7-1	Model 7-2	Model 7-3	Model 7-4
FOUNDER CHAR.				
AGE AT FOUNDING	0.201***	0.067***	0.082***	0.197***
	(0.012)	(0.002)	(0.003)	(0.014)
AGE INTERACTION W/ EXP.		-0.010***	-0.022***	
		(0.001)	(0.002)	
AGE AT FOUNDING^2	-0.002***			-0.002***
	(0.001)			(0.0001)
NUMBER OF STARTUPS FOUNDED			-0.511***	
PRIOR EXPERIENCE CHAR.			(0.086)	
PRIOR ACQUISITIONS				
	-0.334***			
PRIOR IPOs	(0.036)			
	-0.484***			
# SAME STATE	(0.070)			
		-0.084**		
# DIFFERENT STATE		(0.032)		
		0.060**		
SAME 2-DIGIT SIC CODE		(0.022)		
				-1.039***
DIFFERENT 2-DIGIT SIC CODE				(0.159)
				-0.706***
CONTROLS				(0.108)
INITIAL CAPITAL				
	-0.012**	0.009*	0.011**	-0.002
BACHELOR'S DEGREE ONLY	(0.006)	(0.006)	(0.006)	(0.006)
	0.243***	0.288***	0.287***	0.349***
MASTER'S DEGREE	(0.041)	(0.041)	(0.041)	(0.047)
	0.109***	0.137***	0.121***	0.147**
INDUSTRY SEGMENTS	(0.041)	(0.042)	(0.042)	(0.047)
YEAR DUMMIES	YES	YES	YES	YES
Constant	YES	YES	YES	YES
	-2.555***	-0.268	-0.904**	-3.011***
Prob > chi2	(0.453)	(0.382)	(0.397)	(0.474)
Pseudo R-squared	0.000	0.000	0.000	0.000
	0.353	0.464	0.466	0.502

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Model 7-1 shows that *PRIOR ACQUISITIONS* and *PRIOR IPOS* are associated with shorter lags. The significance and negative sign of the squared term on *AGE AT FOUNDING* indicate that the relationship between age and lag is curvilinear and concave. Those with Master's degrees have a shorter lag than those with just a Bachelor's. Model 7-2 adds a term interacting age and prior experience. Both variables remain significant and the interaction term is significant and negative. This indicates that older entrepreneurs show a greater reduction in lag as a result of prior experience. In Model 7-2 the *NUMBER IN THE SAME STATE* has a large significant impact on reducing lag, and the *NUMBER IN A DIFFERENT STATE* significantly increases the lag. In Model 7-4 we find that the number of prior startups in the *SAME 2-DIGIT SIC CODE* is associated with a greater decrease in lag than the number in a *DIFFERENT 2-DIGIT SIC CODE* (both coefficients are significant). All regressions indicate that older entrepreneurs are slower to go through the process from founding one firm to founding the next.

V. CONCLUSION

Do entrepreneurs benefit from similar effects of learning-by-doing found in manufacturing settings? If so, how valid is the knowledge one gains from experiencing a particular situation only one or two times? The results support the main thesis of the article which is that certain characteristics of individuals and of prior experiences appear to contribute to greater learning from small samples of experience. Our primary proposition, Hypothesis 1a, that there are benefits to prior experience even when it is infrequent, is strongly supported. This is the first article which we know of to test this hypothesis in a model controlling for individual fixed effects. Hypothesis 1b was that conditioning on at least one prior founding, current firm performance would be higher with greater numbers of prior founding experiences and the evidence in Table 4 supports this hypothesis. The regression results in Table 7 indicate that older individuals have a longer lag between firms, but show a greater reduction in lag between ventures with each prior experience. Hypothesis 2a was that founders would learn more from prior experiences of success. The data are mixed but tend to support this hypothesis.[15] Model 4-3 indicates that the number of prior acquisitions has a significant positive impact on the likelihood of an IPO. However, we cannot eliminate the possibility that more is learned from failure, yet other mechanisms such as a tarnished reputation affect performance via impact upon potential recruits, financiers and even suppliers and customers.

The regression results in Table 7 and Table 2 show that the ability more quickly to go through the entire process of starting a firm, developing it, executing the exit strategy, recognizing a new opportunity and founding a new startup, appears to be an interesting area for future research. Prior work shows that founding experience aids in raising capital quicker (Hsu, 2007). The results appear to support Hypothesis 2b, that individuals remaining in similar contexts (SIC code and geographic location) benefit more from small samples of experience. The most relevant results here are the relative differences where the reduction in lag for each prior founding experience is reversed for those starting a firm in a different state and there is a greater lag for those changing industrial contexts.

The overall pattern of results, under a number of different specifications and measures, appears to provide robust evidence supporting a learning-by-doing story. However, what explains the lack of significant results in Tables 3 and 4 on the revenues (and employees) measures? One explanation may be that many high-tech firms do not achieve revenues (or ramp up hiring) for the first several years while the focus is on R&D.[16] This interpretation is supported by the significant results for acquisitions and by the results in Table 5 where we find that *PRIOR ACQUISITIONS* is significantly associated with higher revenues once we include controls for the amount of initial capital and venture capital funding.

Robustness and Limitations. An additional empirical implication of a learning mechanism would be that inferences from past experience should be more difficult in complex environments [40, 68]. Both theoretical models of complex, turbulent landscapes, and some empirical work suggests that environmental or task complexity makes learning more difficult and results in flatter learning slopes [19, 69]. Starting a firm in a recessionary market can reasonably be expected to be more complex than starting a firm during a boom time. As a further robustness check, Table 8 shows regression results matching the founding year of the first start-up attempt with various measures of the economic environment. Consistent with reduced learning during complex environments, the results show that the subsequent firms have lower revenues if the first firm was started during a recession (as measured by the National Bureau of Economic Research recession index).

TABLE 8. IMPACT OF ENVIRONMENTAL COMPLEXITY

Independent variables	Dep. Var.=Ln(Revenues)	
NYSE AT FIRST FOUNDING YEAR	4.61E-10**	(0.000)
NBER RECESSION INDEX AT FIRST FOUNDING YEAR	-3.384*	(1.883)
VC DISBURSEMENTS AT FIRST FOUNDING YEAR	-0.033	(0.028)
NUM. OF PRIOR STARTUPS FOUNDED	0.831***	(0.306)
SAME SIC	2.543***	(0.893)
HELD PATENTS	1.352***	(0.349)
AGE AT FOUNDING	-0.022*	(0.012)
NUMBER OF COFOUNDERS	0.283***	(0.095)
OPERATING YEARS	0.067***	(0.023)
LN(INITIAL CAPITAL)	0.349***	(0.051)
VC FUNDED	0.452	(0.360)
MASS. LOCATED	-0.108	(0.271)
CALIFORNIA LOCATED	-0.042	(0.307)
INDUSTRY SEGMENTS	YES	
YEAR DUMMIES	YES	
OBSERVATIONS	629	
ADJ. R-SQUARED	0.392	

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

This article infers learning from examining the coefficient on cumulative start-up experience. Taking this empirical approach yields a highly simplified and stylized learning model. Learning-by-doing is only one of many potential mechanisms for learning by individuals and organizations [68, 70]. Although year and sector dummy variables help

[15] Prior IPOs or acquisitions may be viewed as successes, and are by many other authors, though this largely depends on the valuations achieved.

[16] For many firms undertaking an innovation strategy, significant sales do not occur until after they have undergone an acquisition and a larger firm then deploys their complementary assets to drive production and sales operations.

alleviate concerns that various sources of unobserved heterogeneity drive our findings, this concern remains. One might be concerned that the increases in performance are not the result of learning from prior small samples, but rather from idiosyncratic or lucky private decisions by the entrepreneur about which markets or strategies to pursue. Although this is likely the case on occasion, the prior experience and founder characteristics analyzed would not be expected to have any explanatory power if this was true. It is possible that entrepreneurs view real company performance in terms of high company value or high subjective performance. The current data also may suffer from a self-report bias as both the dependent and some of the independent variables were reported by the entrepreneur. Although we observe a wide range of outcomes and firm sizes, it is likely that we do not observe every startup firm attempted by the entrepreneurs. Serial entrepreneurs showed a slightly higher response rate than one-time only founders and this may have influenced our results. We also cannot ascertain their reasons for deciding to start a new firm or where to locate it. Perhaps current firm performance is lower for entrepreneurs changing states because expectations or a reputation for success or failure alter the decision to move locations. Non-entrepreneurial work experience is another potential source of learning (controlled in our models via age at founding and via individual fixed effects).[17] Unobserved heterogeneity may be influencing our results and including measures of some of these other sources of experience may lead to different conclusions.

Our sample is limited to a survey of founders who at some point attended the Massachusetts Institute of Technology. This is not a random sample of entrepreneurs from the entire population nor were they randomly assigned. Nonetheless, the fact that all the respondents are MIT alumni reduces the concern that there are large differences in wealth, skill, or initial human capital. The lowest quality entrepreneurs may be dropping out of the sample. The concern is partially addressed by research in process that examines the determinants of starting a subsequent firm.[18] Gompers et al. [39] also find higher performance for those with prior entrepreneurial experience but critique a learning-by-doing explanation based on findings that founders with prior success (defined as an IPO) are more likely to be successful (IPO) than first time entrepreneurs. Our estimates in Table 4 control for individual fixed effects and should control for individual differences in time-invariant underlying ability or persistence. A skill vs. luck story where skill is constant over time requires explanation for why revenues appear to continue to increase (and variation decrease) with the number of prior start-ups (successful or not) even when conditioning on at least one prior start-up.

The results indicate substantial benefit from even small samples of prior experience in this setting of founding and developing new firms. Second, older individuals as compared to their younger counterparts appear slightly better at acquiring and using knowledge from small samples of prior founding experience to reduce the amount of time necessary to go through the start-up process.[19] Third, prior experience in the same industry has a positive effect on current firm performance in some models, but seems to have its greatest effect on the speed from founding to acquisition. Areas where entrepreneurs show possible learning effects include the inclination and/or ability to more quickly go through the entire process of starting a firm, developing it, executing the exit strategy, and recognizing and initiating a new opportunity.

Rather than a strict line between exploration with little to no prior experience and exploitation of a familiar area, future work should think more in terms of which components of the experience are familiar [71]. If strategies are discovered for extending learning from small samples, they may also be useful in squeezing even more learning from large samples of experience. Although significant challenges remain inherent in any attempt to learn from sparse samples of experience, a clearer understanding of the issues involved is invaluable for entrepreneurs and policy makers attempting to learn from history. For the literature on learning-by-doing, the results indicate that there are external transfers of learning-by-doing via the exit and subsequent founding activity of the entrepreneurs, even in the context of small samples of relatively heterogeneous events. For entrepreneurs, the results have the implication that it may be preferable to look for co-founders with prior entrepreneurial experience in the same industry and possibly that it is better to start an entrepreneurial career early.[20] The results may also have implications for market structure because they show a mechanism where otherwise proprietary learning-by-doing may be transferred outside of the firm, benefiting entrepreneurial firms and potentially harming the leading firm. Market structure may also have effects on learning [72]. Finally, for policy, the results indicate that programs that encourage early founding attempts or that encourage first time entrepreneurs to use their knowledge gained to found another firm may have significant economic benefits.[21] The contribution of this article is to provide empirical evidence that, even in the context of infrequent tasks and strategic

[17] Lazear's [89] data are consistent with this type of learning hypothesis where having more varied careers may allow individuals to gain diverse enough skills to become an entrepreneur.

[18] The middle range of performers (in terms of revenues) are most likely to start a subsequent firm, whereas both low and very high levels of revenue are associated with a lower likelihood of a subsequent firm (Authors, working paper).

[19] Perhaps wisdom accompanies age and enhances learning capability or the filtering of what pieces of information from past experiences apply to current contexts.

[20] However, caution should be exercised here since the paper does not attempt to determine the impact of prior founding experience in comparison with what would have occurred if the individual gained additional employment experience instead.

[21] Certain types of government intervention have been explored and it appears that regulators can induce learning through light-handed regulation [90].

settings, it may be possible to learn from rare (i.e., small samples of) prior experience.

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APPENDIX A

COMPARISON OF KEY DEMOGRAPHIC CHARACTERISTICS BY SURVEY

Variable	Responded to 2001 survey (N=43,668)	Did not respond to 2001 survey (N=62,260)	*t*-stat for equal means
Male	0.83	0.86	**10.11**
Engineering major	0.48	0.47	**-4.49**
Management major	0.16	0.15	**-5.75**
Science major	0.23	0.23	0.37
Social sciences major	0.05	0.06	**4.07**
Architecture major	0.06	0.08	**11.82**
Non-US citizen	0.81	0.82	**3.77**
North American (not US) citizen	0.13	0.11	**-4.14**
Latin American citizen	0.13	0.12	-1.44
Asian citizen	0.33	0.34	1.45
European citizen	0.30	0.26	**-5.08**
Middle Eastern citizen	0.05	0.08	**6.32**
African citizen	0.03	0.05	**6.25**
Variable	Responded to 2003 survey (N=2,111)	Did not respond to 2003 survey (N=6,131)	*t*-stat for equal means
Male	0.92	0.92	0.12
Engineering major	0.52	0.47	**-3.63**
Management major	0.17	0.21	**4.17**
Science major	0.17	0.18	1.09
Social sciences major	0.06	0.05	1.18
Architecture major	0.09	0.09	1.06
Non-US citizen	0.82	0.81	-1.36
North American (not US) citizen	0.17	0.14	-1.34
Latin American citizen	0.19	0.19	0.13
Asian citizen	0.22	0.24	0.73
European citizen	0.31	0.32	0.38
Middle Eastern citizen	0.08	0.07	-0.59
African citizen	0.04	0.04	0.17

Note: bolded numbers indicate statistical significance at the 1% level.

APPENDIX B

Jovanovic and Nyarko (1995) develop an information-theoretic model that we apply to relate learning by doing to heterogeneity in the performance of entrepreneurial firms. Learning-by-doing has been modeled in a number of different formulations (Muth, 1986, Levitt and March, 1988, Jovanovic and Nyarko, 1995). Nonetheless, it is typically thought of as the result of search for more optimal routines via experimentation and trial and error search. An advantage of this model is that it allows for multiple (N-task) activities each with an optimal level and it has been extended to the case of multiple technologies each with a human capital-specific component. The model links differences in the learning rate to the impact on heterogeneity of firm performance. Another advantage is that the model is agnostic to whether the experienced entrepreneur is accessing better ideas or is able to find more optimal ways to commercialize an idea, holding idea quality constant. It is difficult for our data to tease these apart and although this represents a promising area for future research, the model allows both to be included in a learning-by-doing model. The many technical details can be found in Jovanovic and Nyarko (1995), so we relatively succinctly summarize the model. Entrepreneurs make decisions affecting the efficiency of start-up (production) activity. The efficiency results from how far these decisions are from the optimal values. The efficiency q on the ith start-up (production run) is defined as:

$$q_i = A \cdot \prod_{j=1}^{N} \cdot \left[1 - \left(y_{i,j} - z_{i,j} \right)^2 \right] \qquad (1)$$

where j=1, 2, 3, …, N and N is the number of tasks that activity requires, z_j is the decision for the jth task, and y_j is the "optimal" for the jth task. The maximum level of efficiency is A, and efficiency is maximized at z=y. The ideal level 'y' is a random variable that the decision-makers do not have complete information about, prior to production. Specifically,

$$y = \theta + w \qquad (2)$$

where θ represents the optimal way (on average) to perform the activity, and w represents transitory disturbances that have zero mean and variance σ^2_w. Entrepreneurs know the variance of θ, σ^2_θ, but do not know its mean. Upon founding a firm, entrepreneurs use information gained from the outcome of that founding to revise their estimates of the mean of θ. As the number of start-ups increases (production runs in the original model), entrepreneurs (decision-makers in the original model) have increasingly precise estimates of the mean of θ. However, due to the presence of disturbances, the entrepreneur never knows it precisely. The equation for the expected efficiency of production run τ derived by Jovanovic and Nyarko (1995) is:

$$E_\tau(q_\tau) = A(1- x_\tau - \sigma^2{}_w)^N \quad (3)$$

where $x_\tau = \sigma^2{}_w\ \sigma^2{}_\theta\ /(\ \sigma^2{}_w + \tau.\sigma^2{}_\theta)$. Noting that $x_\tau=0$ as the number of start-ups (production runs) tends to infinity, we can define the eventual expected efficiency as

$$E(q^*) = A(1- \sigma^2{}_w)^N \quad (4)$$

The learning curve in this model is primarily a function of the disturbances in the signal of the optimal decisions, the uncertainty in the optimal decision on each task, and the number of tasks.