Cutting Your Teeth: Building on the Micro-Foundations for Dynamic Capabilities

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Abstract:

Theorizing on the sources of dynamic capabilities has been rare, particularly on the micro-level determinants of capabilities. We look at evidence for a model where cross-functional experience (in this case, founding a firm) results in a more accurate cognitive map of the industry. This paper investigates whether cross-functional experience improves entrepreneurial firm performance via more accurate mental models of the industry landscape. We use detailed data from the MIT Founder’s Survey to test our theory. In addition, we show that a major industry disruption (in the form of the dotcom boom) resulted in the loss of benefit from cognitive maps developed in the prior environment. The results provide evidence consistent with our model of cognitive maps as a source of capability and counter to several alternative accounts.
The question of why some firms develop more valuable resources and capabilities than others has been a central one for strategy researchers. The resource-based view (RBV) of the firm has been a central theoretical framework for explaining heterogeneity in firm performance (Barney, 1991; Peteraf, 1993; Wernerfelt, 1984). There is a growing consensus that differences in firm performance are driven by higher order capabilities to develop or reconfigure bundles of resources that will generate value over time (Teece et al., 1997; Winter). However, we still do not understand the source of dynamic capabilities and why some managers are able to develop more valuable resources than others.

Drawing on evolutionary economics, the existing conceptions of the sources of dynamic capabilities have been guided by relatively passive, inertial mechanisms of incremental, local search (Zott, 2003). The main conceptual framework that has guided work in the literature is variation, selection, and retention of higher order routines that guide local search processes for more valuable bundles of capabilities and resources (Winter, 2003). This literature has argued that firms inherit rule-based mechanisms for choosing a local search method and that firm productivity is a result of the performance of these inherited search routines. Yet, routine-based theories of managerial behavior have long been thought by scholars to be entwined with more cognitive logics (Gavetti, 2005; March and Simon, 1958, March and Olsen, 1976). Some scholars began to point out important limitations and difficulties arising from local search experience (Gavetti and Levinthal 2000, Levinthal & March, 1993).

A growing literature examines how managers may play a more active, cognitive role in predicting which resources and capabilities will be more valuable than others. This literature emphasizes an approach considering the imperfect cognitive representations that limit the link between choices and intended consequences. Studies exploring various decision biases have
been numerous (Camerer, 1995, Nisbett and Ross, 1980, Tversky and Kahneman, 1992, Kahneman and Lovallo, 1993, Kahneman and Tversky, 1979, Kahneman, Slovic and Tversky, 1982, Fox and Hadar, 2006). Managers face numerous biases as they attempt to understand the competitive environment and its trends in enough detail to search for an effective strategy and cluster of resources that will provide competitive advantage (Gavetti and Rivkin, 2007).

Representations have been identified by prior research as important in shaping decision-making as well as focus and interpretation (Huff and Jenkins, 2002, Fiol and Huff, 1992, Walsh, 1995, Simon, 1991, Weick, 1995, Narduzzo, Rocco and Warglien, 2000). The idea that members of the top management team have variation in the complexity of their “cognitive maps” of the industry is not new to the literature (Calori, Johnson and Sarnin, 1994). We extend and build on prior research that has suggested that differences in managerial cognition lead to variation in strategic decisions (Tripsas and Gavetti, 2000, Adner and Helfat, 2003, Holbrook, et al., 2000). However, existing work has focused on the content of mental models rather than on the use of mental models for certain capabilities, such as predicting what resources will be more valuable in the near future.

This paper addresses the gap in our understanding of the sources of dynamic capabilities by conceptually linking the individual and firm levels. Extending the line of work that recognizes that strategy exists in managers’ minds and arises from their cognitive theories about the world (Gavetti and Rivkin, 2007, Huff and Jenkins, 2002, Porac, Thomas and Baden-Fuller, 1989), we suggest a novel mechanism through which dynamic capability arises from improved cognitive maps of the industry landscape. We assert that improved cognitive maps of industry trends and causal relationships come from specific types of industry experience and guide the recombination of resources, routines and capabilities. We respond to calls in the
literature for a research agenda to build the behavioral foundations of our understanding of the causal mechanisms driving the evolution of capabilities as well as the sources of inertia that dynamic capabilities are meant to overcome (Gavetti 2005).

**Theory: Evolutionary Theory and Bounded Rationality**

When organizations are in the act of assembling new bundles of routines and capabilities, what determines who puts together the more valuable and difficult to imitate bundles? Is it passively inheriting better local search routines/processes or is it actively finding more valuable bundles through more accurate cognitive maps of the competitive environment? The recognition that an impossibly large set of information about the world is required for a strictly rational conception of the decision making process led to the concept of bounded rationality to label this constraint on individuals (Simon, 1955). Two research streams emerged around mechanisms for dealing with the constraint of bounded rationality. One emphasized a history-dependent, experiential route of discovery, specialization via local search and the development of stable routines (Herriott, Levinthal and March, 1985). However, The current paper responds to calls in the literature recognizing the need to integrate psychological theory and the determinants of less biased representations under the cognitive foundations of dynamic capabilities.

Gavetti and Rivkin (2007) examine the choice of search mechanism by managers and theorize that the use of specific choice mechanisms is driven by environmental ambiguity (reduced with industry maturity) and firm inertia (increased with firm age). However, less attention has been devoted to the psychological biases and determinants of finding more valuable clusters of resources and capabilities within specific search strategies. Within cognitive search, what mechanisms lead to more accurate representations of the competitive
environment and accumulation of more valuable capabilities? Gavetti (2005) further develops cognition as a micro-foundation for the development of capabilities by delineating a model where managers’ cognitive representations of their environment drive organizational search and capability development. He examines the role of the location of an individual within an organizational hierarchy and theorizes that action generates information which contains signals about the environment and the relationships between actions and outcomes. These signals are then passed up the hierarchy and depending on the divisional structure and the similarity in product lines, individuals at the top or bottom of the hierarchy may develop more accurate cognitive representations. More accurate representations help guide the organizational search for more valuable combinations of capabilities.

**Psychological Theory and Competitive Advantage**

In addition to the location in an organizational hierarchy, other factors are likely to either bias cognitive representations or yield more accurate ones and more profitable combinations of capabilities. Psychological theory offers several alternative mechanisms that help to build our understanding of how to integrate individual-level psychological factors with firm-level dynamic capabilities and competitive advantage. Cognitive representations can be thought of in terms of NK models where sets of decisions correspond to different performance levels or peaks (Gavetti and Levinthal, 2000). They can also be thought of in terms of the subjective probabilities that individuals give to various events or the relationships between actions and the likelihood of specific outcomes. These representations can be inaccurate or overly simplified in several ways.

First, we know from work on availability heuristics that instances that can be easily recalled or scenarios that can be constructed with ease tend to bias the judged probabilities of
such events upward from reality (Tversky and Kahneman, 1973). People with less domain knowledge tend to rely on the ease of recollecting instances, whereas domain experts tend to be biased as well by the number of cases that come to mind (Ofir, 2000). Either way, the bias produced is in the same direction and has been found in multiple studies (Ofir, 2000, Fischhoff, Slovic and Lichtenstein, 1978, Russo and Kolzow, 1994, Dubé-Rioux and Russo, 1988, van der Pligt, J., Eiser and Speark, 1987). The availability heuristic has been used to explain the “pruning bias” where individuals are given a set of categories containing reasons why, for instance, a car might fail to start (or why a business might go bankrupt). When the researchers “prune” categories and absorb them into the residual category, respondents appear to distribute the probability from the pruned categories across the remaining ones rather than add it to the residual category. Pruning bias can also be explained by a different bias known as partition dependence (Fox and Clemen, 2005). Partition dependence is the term given to the phenomenon where assessed probabilities given by individuals for events can vary substantially with the way that the researcher partitions the categories. The phenomenon is similar to framing, the psychological bias where decisions have been shown to be influenced by the way in which alternatives are presented (Tversky and Kahneman, 1986). Psychological theory and research typically attempt to identify universal, generalizable, systematic biases in human decision-making rather than to identify which individuals may be more or less prone to biased perceptions and decisions. Similarly, in theories of dynamic capabilities and resource-based view, no individual has a more accurate cognitive representation of the competitive landscape than anyone else. However, given the prior research in psychology cited above it seems likely that some managers may hold more accurate and/or less biased cognitive maps or sets of
subjective probabilities than others. This is particularly true if different demographic
c Characteristics or work experiences lead to less bias in cognitive representations.

Individuals have varied educational and career experiences that may result in more (or
less) biased perceptions, representations and thus strategic decisions. A rapidly growing area
of literature examines prior career experience (Beckman and Burton, 2008, Boeker, 1989,
Haveman and Cohen, 1994, Haveman, 1993, Phillips, 2002). A large section of this work has
been interested in the knowledge, aspirations, skills, or routines that employees inherit from
their firms (Agarwal, et al., 2004, Ciuchta, et al., 2009). However, employees may gain more
than just task knowledge, skills or routines from their firms, they may also acquire cognitive
representations of the competitive environment which have varying accuracy. A key question
is whether variation in career experiences might give rise to variation in the extent of the
psychological biases that affect perception and decision-making.

Lazear (2004) argues that an important determinant of entrepreneurship is the breadth of
an individual’s curriculum background and number of different jobs. While the paper argues
that leaders and entrepreneurs need a variety of skills, the study raises the question of the
mechanism behind the correlations. Another interpretation is that more varied job role
experiences are a source of diverse perspectives on the industry and more varied sources of
signals from the environment. This benefit from a wide range of functional experiences could
be due to the more diverse signals from the competitive environment that the individual
receives as much or more than it is due to a diverse set of skills or routines. An individual
working on a single functional area may take actions and scan the environment for relationships
between those actions and outcomes that form the basis for her beliefs about the competitive
environment. Daft and coauthors (1988) have shown that scanning the environment is an
important activity for company performance. Recent work experience that is heavily focused in a single, narrow functional domain can result in more focused attention on a subset of the competitive environment (for example, technology, to the neglect of shifting markets). The result is more detailed partitioning of that sub-area while other functional areas of the landscape become less evenly partitioned and detailed in the cognitive representation. The other areas are less available to the mind in search and decision making over what capabilities will result in competitive advantage over time. More detailed partitioning of one sub-area leads to underweighting the probability and importance of constraints and negative events from other functional areas. In this way, strategic search and the bundles of capabilities a manager chooses to develop are likely to be optimized for one domain. The individual for whom cognitive partitions are more detailed in one area and constraints related to that function are more accessible will be resistant to strategic options that may fit constraints elsewhere but are less ideal in the domain where they have years of work experience.

However, for an individual, such as a founder or CEO who has responsibilities and decision rights that span multiple functions, the scope of scanning and monitoring the relationships between actions and outcomes in the industry must be much wider. While depth may be lost, a sense of the landscape of the competitive environment through multiple functional lenses (i.e., marketing, technology, finance, etc.) develops and must be integrated. Work experience that includes responsibilities simultaneously spanning multiple functional areas is particularly important for ongoing competitive advantage. The reason is that for individuals who rotated through functional roles one at a time over multiple years, their cognitive representations of customer trends or relevant technological shifts in the industry are likely to be several years out of date if they held those positions many years in the past. For the
purposes of using cognitive maps to search for bundles of resources that will be valuable in the coming years, current beliefs and knowledge of industry trends is necessary. An individual in a position to perceive industry trends and constraints through multiple functional lenses in an up-to-date fashion will have more accurate cognitive representations of trends and a greater likelihood of identifying groups of capabilities that can be developed to profit from those trends. Similarly, in academic fields, a lay-person can read the most recent scholarly articles, but without actually participating in research, making decisions on projects and getting feedback at conferences, it is difficult to develop a sense for the direction that the field is headed and to anticipate shifts that will be important (Cohen and Levinthal, 1990).

If communication is imperfect across individuals, then there should be benefits to diverse functional experiences within the same individual rather than across a team. Prior work supports the idea that there are imperfections in communication across groups, incurring process costs that reduce efficiency and group output (Kurtzberg and Amabile, 2001, Steiner, 1972). The idea that individuals and teams with more diverse information may outperform others has not been connected systematically to psychological theories or to differences in mental models (Taylor and Greve, 2006). All else equal (including team size and conflict), teams with more cognitive diversity tend to be more creative and have higher performance (Milliken and Martins, 1996, Chatman, et al., 1998, Jehn, Northcraft and Neale, 1999, Harrison, et al., 2002, Williams and O'Reilly, 1998). When diverse experiences and cognitive approaches are combined in a single individual, the knowledge becomes more integrated. In addition, the coordination and access problems characteristic of teams are not present, yielding higher performance. The counter argument is that the diverse team members are likely to have
higher expertise and knowledge in each of their areas of functional diversity. Then, despite the communication effect, overall team benefits might be higher.

Hypothesis 1: Individuals with more cross-functional experience will found firms with higher performance via more accurate industry representations.

In psychology, a transfer effect is the beneficial impact of a prior event on the performance of a subsequent event (Finkelstein and Haleblian, 2002). The similarity between the characteristics of events influences the probability of positive outcomes from transfer (Argote and Ingram, 2000). The probability of negative outcomes can increase when events are dissimilar yet lessons from prior experience are applied anyway (Finkelstein and Haleblian, 2002). We suggest that a distinct but related mechanism to transfer effects occurs between individual representations and the organizational levels of analysis. Typically transfer effects involve learning a skill in one context but with a loss of performance when the skill is wrongly applied in a different context. However, different from learning specific knowledge or a skill, even if transfer is perfect, cognitive maps honed on one competitive landscape will lead to errors when brought to guide firm strategy in a new landscape. One can have a nearly perfect map of one country but it is of no use in discerning the topography of a different country.

Previous literature argued that 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 (Cohen and Bacdayan, 1994, Zander and Kogut, 1995). As Gavetti and Rivkin (2005) indicate, the problem in the case of forming strategy by analogy is that strategy development requires both a breadth of prior experience (which may not be available) and a good fit between the relevant
dimensions of the current, novel situation and the prior situation. Inferences may be misapplied or the wrong inferences may be drawn from the beginning (Finkelstein and Haleblian, 2002). Along these lines, we argue that cognitive representations developed in one context will not aid strategic search in a substantially different context. Furthermore, examining the impact of the similarity of experience will allow us an additional test of whether higher performance for subsequent firms is a result of improved representations or of higher skill levels. Unless higher skill individuals 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 supports better cognitive maps as the correct mechanism.

Hypothesis 2: Cross-functional experience will lead to less cognitive inertia from remaining in similar contexts and higher performance for those remaining in the same industry.

Whether an event turns out as a success may influence what knowledge about the competitive landscape the individual takes away from a previous experience and how she or he applies that knowledge to future situations (Cyert and March, 1963). Politis (2005) 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 (1999) emphasizes 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 (March, 1991). Starbuck and Hedberg (2001) 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

1 Indeed, Henderson and Clark (1990) argue that if the environment is characterized by demands for innovations in the firm which do not match the organizational architecture of the manager’s prior experience, learning by analogy may prove difficult.
of learning. We elect not to hypothesize about failure directly since identifying failure is often difficult. For example, is it a failure to shut down a firm quickly rather than to continue it when a better idea is identified? The literature appears somewhat mixed on whether more knowledge is gained from success or failure. However, prior arguments have neglected one important mechanism that yields improved cognitive representations from success experience, but not from failure. When an individual experiences significant success others often come to that person to seek their advice or involvement in new opportunities. This is less true for those who have failed. The flow of other individuals proposing new ideas not only increases the number of opportunities examined but may increase the detail and accuracy of representations through a sharp increase in the signals of trends in technology, competitors, and/or markets. It is clear that individuals do learn from failure as well as success and that learning from failure can enhance survival (Kim and Miner, 2007). Yet those who have failed lack this rich source of improvements in their cognitive map that may be more important for identifying new capabilities over and above just surviving.

Hypothesis 3: Cross-functional experience will lead individuals who have experienced success to continue higher performance.

**Empirical Strategy and Setting**

Finding a setting where we can empirically isolate the impact of cognition separately from the inheritance of routines or resources is challenging. Attempting to test our hypotheses in a sample of existing large firms would be problematic for several reasons. One is that the original founders who guided the initial conditions and strategic search when inertia was lower may no longer be around to respond to questions. Second, the selection mechanisms may be far from clear as to which managers are assigned to which projects and how much of the
performance of those projects is due to the formal or informal control of managers in specific locations in the hierarchy. Using existing public firms only also introduces survival bias. Finally, transfer of resources or existing capabilities from other business units in the firm makes it challenging to identify the effects that interest us. These challenges mean that no dataset will be ideal along all dimensions; however, a novel survey allows us to make empirical progress, particularly on individual-level data and multiple measures of firm performance where prior work has largely relied on simulation analysis.

The idea of organizational inertia is that elements of the organization are surprisingly resistant to change once established early in the life of the organization (Baron, Hannan and Burton, 1999, Hannan and Freeman, 1984). The closely related idea of imprinting is that both environmental conditions at founding and strategic decisions made by the founders early on are not easily reversible and leave a lasting imprint on the firm’s subsequent development (Stinchcombe, 1965, Romanelli, 1989, Romanelli, 1991). For example, it has been shown that subsequent top manager backgrounds and later functional structures can be predicted by the founding team’s prior functional experiences and initial organizational functional structures (Beckman, Burton 2008). In addition, the initial incumbents in functional positions appear to imprint those positions in certain ways that are strong enough to condition the likelihood that the subsequent holders of those positions may leave for other firms (Burton and Beckman, 2007). These studies provide evidence that founders bring blueprints or models that then shape the future directions of the firm (Baron, Burton, Hannan 1999). Other evidence shows that resources accrue to individuals and firms based at least partly on the structural positions of their former employers (Burton, Sørensen and Beckman, 2002).
In the model of Gavetti (2005) cognitive representations then guide search mechanisms and become important initial conditions that imprint the future directions of development for the company (Baron, Hannan and Burton, 1999, Stinchcombe, 1965). Furthermore, organizations are known to become less plastic as they age (Hannan and Freeman, 1977) so the cognitive maps available to managers in the beginning stages of developing a new business line or new venture are vital since hiring individuals with higher quality cognitive representations after inertia has set in will have less of a payoff. If more accurate cognitive representations of the competitive landscape function as dynamic capabilities that improve firm performance, then this is a source of competitive advantage which other firms clearly would not be able to imitate. It is impossible for competitors to go back in time and replace the founders with others who had different experiences and beliefs about the competitive landscape.

**Data and Methods**

At the founding of a new firm, resources are limited and existing firm capabilities are non-existent, allowing us to better isolate the impact of mental models developed from prior work experience. The founders are a key input at the beginning stages of a firm and other work shows the importance of founders in framing the initial conditions for strategic search (Gavetti and Rivkin, 2007).

Our identification strategy begins with the selection of the setting of company founders as a more narrow and ideal empirical sample to test our hypotheses because of the factors discussed above. In particular, it better allows us to isolate the impact of routines vs. cognition from the complicating factors of existing firm capabilities and resources that would otherwise impair the identification of the effects we hypothesize about in other settings.
We take advantage of both differences between those who have and have not had the experience of founding a firm as an indicator of cross-functional experience. Those who have worked in established companies are much more likely to have worked in a single functional domain at a time (unless they were CEO), whereas we know that those who were founders almost surely had work experience that crossed functional boundaries while founding the firm. We also take advantage of differences between those with multiple episodes of cross-functional work experience (multiple firm foundings) as compared with those who have only had one experience. Those individuals with more cross-functional experience compared to those with less offer another identification strategy. If an episode of cross-functional experience is thought of as the treatment effect, then we look both at differences between the treated and untreated as well as difference between those individuals with more episodes of the treatment effect compared to those with fewer. Finally, we use the panel structure of data on firm foundings over time to rule out several alternative explanations that remain plausible after the initial analyses. In particular, a strong advantage of our setting will be that we can provide evidence that we are not seeing a selection effect rather than the treatment effect. The panel structure of the founder data where we have entire founding histories allows the use of individual fixed effects for those who have founded more than one firm so that we can control out the possibility that more persistent or higher ability individuals choose to found more firms.\(^2\)

We use a novel survey administered in 2001 to all 105,928 alumni from a prestigious research- and technology-based university in the United States to generate a sample of firms

\(^2\) The individual fixed effects allow us to rule out the selection effect (time-invariant individual characteristics) in going from fewer episodes of treatment to more, but not in going from no treatment to treatment (no cross-functional experience to one prior founding). A Heckman selection model might help with the latter concern, however we lack the requisite exclusion restriction (something correlated with entrepreneurship but not with performance) required for this identification approach.
where we have detailed information on founders as well as on firm performance. This survey generated 43,668 responses. Out of 7,798 alumni who had indicated that they had founded a company, 2,111 founders completed more detailed surveys in 2003, representing a response rate of 25.6%. 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. Each founder reported information on up to five firms which he or she had founded up to the date of the survey, yielding a total of 3,698 firm observations. On average, 1.79 firms were 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 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 firms. To provide still more information about these companies including current sales, employment, industry category and location, this new database was further updated to 2006 data from the records of Compustat (for public companies) and Dun & Bradstreet (private companies). For consistency in the country and institutional context, the 1,121 firms that were founded outside of the U.S. were dropped from the analyses reported in this paper. Information on sales was adjusted for inflation to constant dollars.

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3 Hsu et al. (2007) show 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.

4 Successful matches were found for 80% of the company names in the D&B database. A firm is included in the Dun & Bradstreet database when it needs to obtain a credit rating. An analysis of Dun & Bradstreet's coverage compared to other sampling sources for small businesses concluded that there was not a bias towards larger firms (Aldrich, et al., 1989).
Although teams of multiple co-founders are more likely to start a new firm, as well as be more successful in their firms (Roberts, 1991), 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 (Ruef, Aldrich and Carter, 2003) 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 multi-company founder chose only 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 allow the final number of observations to vary by the analysis in order to utilize all available data. Meaningful numbers of foundings begin in the 1950s, therefore we restrict our analysis here to firms founded from 1950-2001. A key feature of this dataset is its long time horizon allowing us to analyze almost entire careers.

Dependent Variables. Because our focus is on measuring the performance effects of variation in the cognitive representations that come from work experience, we use revenues, acquisition, IPO, employees, and lag between foundings as the dependent variables. No single outcome measure is ideal.\footnote{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. Organizational performance of firms is likely to be a noisy proxy for a more accurate cognitive map. Nonetheless, because the prior work 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 it to be detected, cognitive maps must be more accurate in such a way as to impact performance in a large sample of organizations.} 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 use the fact of an IPO as a measure of success (Gompers, et al., 2006, Shane and Stuart, 2002). But far more firms experience acquisitions rather than exit via IPOs. It is important to recognize that performance is multidimensional in nature (Chakravarthy, 1986). 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.\(^6\) 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).\(^7\) Lag Between Subsequent Firms is the number of years from founding one firm to founding the next firm. We use acquisition in event-history models as well.

Independent Variables. We use independent variables related to the characteristics of the founder and the nature of the prior experience, as well as a number of controls. The key independent variable is our proxy for the number of diverse (simultaneous) functional

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\(^6\) Adjusting for inflation is not entirely necessary since year dummies are used; however they were already calculated for use in descriptive statistics.

\(^7\) 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 (1,424 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, whereas 18.8% of the non-responders had been acquired.
experiences and a greater span of functional decision rights, the number of start-ups previously 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. We argue that the main difference is that founders who have had prior experience in a small, entrepreneurial firm are more likely to have utilized general skills and to have had a wider range of responsibilities compared to individuals in larger firms who typically have had more narrow functional roles. Prior work has already shown that entrepreneurs and leaders appear to invest in more general human capital and diverse experiences relative to others (Lazear, 2004). We expect that those who have been CEOs would similarly build more balanced cognitive maps as a result of their multi-functional experience. However, they also have much higher opportunity costs relative to most employees so that would simultaneously influence the performance of the projects they select to pursue. 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 cross-functional experience. 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. Managers cannot truly gauge the ultimate success of their actions until the final outcome is known.

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8 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%. 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.
Individuals also differ in their starting human capital and in particular in the number of years of education they have received. We include dummy variables indicating whether the individual’s highest degree was a Bachelor’s degree, Master’s degree or Doctorate. As a measure of success experience, we use Prior IPOs, 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 firms which have been acquired. Although survival is often used as a performance measure, survival exists among underperforming firms (Gimeno, et al., 1997). 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 (Dushnitsky and Lenox, 2005).

Control Variables. Some of our analyses use a set of industry dummies as 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. 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, defined as capital raised within the first year after founding). VC Funded is equal to 1 if the individual reported raising funds from venture capital firms.
Results

Descriptive statistics are presented in Table 1.

Multivariate Regressions on Firm Performance

We use multivariate regressions beginning with a baseline model followed by results controlling for factors that may be confounding the results including: 1) time-invariant individual fixed effects and 2) specific firm characteristics, social networks, and fundraising. We then further reinforce the results by testing whether better representations may lose their value once there has been a significant disruption to the industry environment.

Baseline regressions

To test the influence on firm performance of different types of prior experience we use a variant of a production function modified to better fit the case of younger firms. Traditionally we would write an equation of the form:

\[ Y = F(K, L, X) \]  

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 private firms, output and capital in particular are extremely difficult to measure for a number of reasons.\(^9\) Cognitive representations of the industry resulting from varied prior experience of the founders are considered an “input” into the firm formation process in the sense that a more accurate cognitive representation increases

\(^9\) 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 performance that we are interested in measuring.
performance (controlling for the level of labor and capital) by acting as a dynamic capability. First we use the baseline multivariate regressions shown in Table 2. The specification of the regression model is as follows:

\[ y_{it} = \Phi(\beta'x_{it}) \]  

(2)

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 foundings. 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 (2-1), acquisition (2-2), initial public offering (2-3), employees (2-4), and operating years (2-5).

In Model 2-1, 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. Male gender and advanced degrees are significant. Model 2-2 shows that the number of prior start-ups that had been 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 are also correlated with higher likelihood for an acquisition. In Model 2-3, none of the key independent variables are associated with the likelihood of an IPO. But again, greater numbers of employees, older firms, and being located in Massachusetts or California are correlated with higher likelihood of an IPO. Looking at the number of employees as the dependent variable, Model 2-4 shows that the number of prior firms in the same industry is associated with a larger firm size. Finally, Model 2-5 shows that with more prior founding
experience, individuals appear to close subsequent firms more quickly. This is consistent with more accurate cognitive maps revealing to the founders more quickly that the opportunity can no longer be successfully executed (or increasing opportunity costs of running an underperforming firm with higher levels of start-up experience).

Effects of a Major Industry Disruption

If more accurate mental models of the industry are the mechanism driving our results, then after a significant disruption to an industry then we should see that the benefits are lost. We use the major disruption to the software industry of the internet boom during the late 1990s to test this idea. Narrowing the sample to only software entrepreneurs, Table 3 tests whether the effect of cross-functional experience remains after the internet boom. The results show that post-1997 the impact of cross-functional experience became negative and significant as individuals who had built up mental models before the internet boom mistakenly attempted to apply them after the disruption to the industry. Similarly, when we separately ran the analysis on the pre-1997 time period and post-1997 time period, the coefficients on cross-functional experience are positive and significant for the pre-time period and are significantly lower (indistinguishable from zero) for the post-1997 time period. These results are consistent with the mechanism of cross-functional experience leading to more accurate mental models (which are disrupted by a major industry shift) but not with alternative interpretations.

Controls for Individual Effects
Although intriguing, these results are not conclusive, mainly due to the lack of controls for time-invariant individual level differences which may be correlated both with the likelihood of founding additional firms and with performance. 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 start only a single firm (Gompers, et al., 2006). If on average 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 return to wage employment. 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.\(^\text{10}\) 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. If there is an improvement in the accuracy of cognitive maps leading to competitive advantages (in addition to differential skill levels), then conditioning on high persistence (more than one firm founding) we expect to continue to observe higher performance with prior foundings.

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 that capture time-invariant differences in individuals which may include higher underlying skill, persistence, family wealth, or preferences for variety, all of which are likely confounding the earlier estimates. Again, Model 4-1 finds that the prior start-

\(^{10}\) 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.
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, but 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 that causes individuals to be quicker in shutting down bad firms.

Controls for Detailed Firm Characteristics

The analysis thus far is supportive of hypothesis 1. However, using the panel data we lack information on certain control variables that may be important as resource differences such as the amount of capital raised, the number of co-founders and whether the firm received venture capital funding. It may be that those with prior founding experience are better able to raise capital or to attract more co-founders. 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, and other aspects of the firm. 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).

In Table 5, we start with a baseline model (5-1) which tests the effect of the number of startups founded on the revenues of the current firm with age at founding, Bachelor’s degree, Master’s degree, as well as the controls included. The effect of prior founding experience on revenues is positive and significant. In Model 5-2, the coefficient on number in the same state is significant and shows that these prior firms each contribute positively to the current firm’s revenues. Prior startups in different states lack a significant impact on the current firm’s revenues. This effect may support the social network benefits explanation as opposed to the one we are advancing; however, it may be due to the smaller sample size of founders changing states. The total number of founders shifting states between the current startup and the prior founding is 172 and the number that we know remained in the same state is 382. Model 5-3 shows that the number of prior startups in the same 2-digit SIC code is associated with higher performance and the coefficient is significant. In Model 5-4 we find that the number of prior acquisitions has a positive coefficient and is significant but the coefficient on prior IPOs is not significant (there were only 84 prior IPOs linked to 72 different founders). Since there is a moderate degree of pair-wise correlation between these various counts of prior experience, we ran these as separate models. Model 5-5 includes an interaction term showing that those with Master’s degrees benefit more from each multi-functional experience. Model 5-6 show that the results on the number of multi-functional (start-up) experience hold even when the number of functions (marketing, engineering, etc.) on the founding team are controlled. The results were
also consistent with the hypotheses when using event history analysis to examine the probability of acquisition rather than revenues as an outcome measure (Cox, 1972).

**Robustness and Limitations**

Starting a firm in a recessionary market can reasonably be expected to be a different context than starting a firm during a boom time. As a further robustness check, (available from the author) shows regression results matching the founding year of the first start-up attempt with various measures of the economic environment. The results are consistent with the idea that representations of the industry built during unusual economic conditions may be less helpful when the environment shifts to a more stable condition. 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).

There are a few alternative accounts worth noting. Empirical work has begun to explore learning from rare events with intriguing, yet mixed results (Denrell, 2003, Kim and Miner, 2007, Zollo and Singh, 2004; Baum and Dahlin, 2007). Some have suggested that learning rates may be higher in slightly heterogeneous settings (Haunschild and Sullivan, 2002, Schilling, et al., 2003). However, it seems unlikely that the results are explained entirely by individuals learning the generic set of skills required for founding a firm. If this were the case, then we would expect those skills to transfer to different industries and across states.**11**

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**11** The entrepreneurship literature is beginning to focus on the process of learning among entrepreneurs. Politis (2005) 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 (Alsos, 1998, Westhead and Wright, 1998) while others show performance advantages for multiple entrepreneurs (Gimeno, et al., 1997, Stuart and Abetti, 1990). Although they argue against a learning interpretation, the work most closely related to this article is that by Gompers, Kovner, Lerner, and Scharfstein (2006). 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
would also expect that conditioning on one founding experience, individuals would have picked up most of these entrepreneurship-specific skills and would benefit less from subsequent experiences. Nonetheless, future work should more directly test the idea that functional work experience leads to differences in biases and cognitive maps relative to multi-functional experience.

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. Gompers et al. (2006) also find higher performance for those with prior entrepreneurial experience but critique a learning 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. Our data do not come from a random sample from the entire population. Nonetheless, the fact that all the respondents are alumni of a prestigious research- and technology-based university reduces the concern that there are large differences in wealth, skill, or initial human capital.

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 even more than do the opportunities to be acquired. 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.

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).
Conclusion: Do firms gain a competitive advantage through dynamic capabilities in the form of improved cognitive representations?

Do firms gain a competitive advantage through dynamic capabilities in the form of improved cognitive representations which the founders acquired via prior work experience? The results support the main thesis of the paper that the answer is yes, they do. Our primary proposition, Hypothesis 1a, that individuals with more diverse experiences and a greater span of functional decision rights will build more accurate cognitive representations, resulting in assembling more valuable combinations of resources/capabilities was supported. Hypothesis 1b was that those with higher information processing capacity will build more accurate cognitive representations. Hypothesis 2 was that founders would build more accurate cognitive representations from prior experiences of success. The data tend to support this hypothesis.13 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 accurate representations result from failure, yet other mechanisms such as a tarnished reputation affect performance via impact upon potential recruits, financiers and even suppliers and customers. The overall pattern of results, under a number of different specifications and measures, appears to provide robust evidence consistent with an account where experience with a broader set of responsibilities and functional decision rights leads to more balanced representations to guide strategic decisions.

However, what explains the lack of significant results in Tables 2 and 4 on the revenues (and employees) measures? One explanation may be that many high-tech firms do not achieve

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13 Prior IPOs or acquisitions may be viewed as successes, and are by many other authors, though this largely depends on the valuations achieved.
revenues (or ramp up hiring) for the first several years while their focus is on R&D.\textsuperscript{14} This interpretation is supported by the significant results for acquisitions and by the results in Table 5 where we find that the number of prior acquisitions is significantly associated with higher revenues once we include controls for the amount of initial capital.

Differences in the accuracy of cognitive representations, particularly concerning trends and shifts in the competitive landscape may also be a reason why individuals voluntarily leave firms. Individuals may choose to move to other firms or start their own new ventures when disagreements arise, when they see opportunities others do not, or when the existing firm seems incapable of exploiting quickly due to inertia or loss of plasticity (Klepper and Sleeper, 2005; Klepper, 2007). The current paper makes its contribution in examining a different cognitive spillover mechanism: Where individuals appear to transfer to a subsequent firm more accurate representations as a result of the prior founding experience. Our account also provides a complementary theory of why managers and entrepreneurs may leave and go outside of their firms to work for others or to start their own ventures. Most organizations tend to become more rigid over time. If individuals within the same firm can develop substantially different cognitive representations of the competitive landscape due to differences in types of experience and the accumulation of psychological heuristics/biases, then individuals can begin to have fundamental disagreements with the organization. Furthermore, due to the inertia and rigidity of the existing bundles of capabilities, it becomes increasingly difficult to move the organization to a new set of resources and capabilities that individuals perceive will provide competitive advantage according to their representations of the competitive landscape. Some individuals leave for new organizations due to increased rigidity in bundles combined with

\textsuperscript{14} For many firms undertaking an innovation strategy, significant sales do not occur until after they have been acquired and a larger firm then deploys its complementary assets to drive production and sales operations.
cognitive maps drifting away from the increasingly small set of recombinations possible within
the firm or from an inability to convince others to select their bundles of capabilities.

While this moves our understanding forward, we still lack a psychological foundation
for identifying where differences arise in cognition or beliefs about the future value of routines,
resources or capabilities. Specifically, we extend the microfoundations of strategy (Gavetti,
2005) and seek to answer the question: When organizations are putting together new bundles of
routines and capabilities, what determines who puts together the more valuable and difficult to
imitate bundles?

Differences between firms in the resources they have gathered through superior
information or luck generate differences in firm performance. Competitive advantage is
sustained to the extent that competitors can be prohibited from replicating or substituting for
the key valuable resources. Other scholars have put forth specific isolating mechanisms such as
path dependence, social complexity, causal ambiguity and firm specificity that keep resources
from being easily imitated (Rumelt, 1991, Hatch and Dyer, 2004, Dierickx and Cool, 1989,
Lippman and Rumelt, 1982).

We build on the theoretical framework for the psychological foundations of
capabilities’ development laid out around cognition by extending the theory to propose
mechanisms by which differences in cognition emerge. We then empirically test whether these
differences result in performance differences among firms (Gavetti and Rivkin, 2007, Gavetti,
2005).

Extending earlier efforts to disaggregate the influence on business-unit profits of
industry, corporate-parent and market share effects, scholars have examined the influence of
firm-level effects (Schmalensee, 1985). Examining lower levels of analysis shows that
industry-level effects are approximately half as important as business effects in determining business-unit profits (Rumelt, 1991, McGahan and Porter, 1997). Yet, with the exception of work on top management teams and entrepreneurship, much less work has looked at the influence of even lower levels of analysis (including individuals) on performance (Higgins and Gulati, 2006, Johnson, 2007, Mollick, 2008). Why do some firms outperform others even when in the same industry? Prior work has shown that individuals with firm-specific human capital can be a source of competitive advantage (Hatch and Dyer, 2004). Our contribution is to use psychological foundations to show how even industry-specific (not firm-specific) representations embedded in individuals can function as a difficult to imitate dynamic capability, guiding firms to build competitive advantages. Similarly, we lack a theory for why the managers of firms become motivated to change the bundles of routines and capabilities in certain ways and for how they know in what directions to change them.

In conclusion, we have developed and tested a model that links psychological theory to dynamic capabilities and heterogeneity in firm performance. Variation in career experiences leads to variation in the extent of known psychological biases such as availability and partitioning dependence, and then variation in the extent of these biases results in differences in cognitive representations that function as a dynamic capability providing a map to future bundles of resources that will provide a performance advantage.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log revenues</td>
<td>1264</td>
<td>14.05</td>
<td>3.08</td>
<td>0.03</td>
<td>21.66</td>
</tr>
<tr>
<td>Acquired</td>
<td>1840</td>
<td>0.19</td>
<td>0.39</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>IPO</td>
<td>1790</td>
<td>0.11</td>
<td>0.32</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Lag between</td>
<td>1502</td>
<td>12.11</td>
<td>9.41</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>Number of Firms</td>
<td>2058</td>
<td>1.61</td>
<td>1.30</td>
<td>1</td>
<td>11</td>
</tr>
<tr>
<td>Prior Acquisitions</td>
<td>2067</td>
<td>0.13</td>
<td>0.42</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Prior IPOs</td>
<td>2067</td>
<td>0.04</td>
<td>0.23</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Prior Same SIC</td>
<td>1473</td>
<td>0.02</td>
<td>0.14</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>Prior Different SIC</td>
<td>1473</td>
<td>0.02</td>
<td>0.18</td>
<td>0</td>
<td>3</td>
</tr>
<tr>
<td>Prior Foundings in the Same State</td>
<td>2067</td>
<td>0.38</td>
<td>0.90</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Prior Foundings in a Different State</td>
<td>2067</td>
<td>0.23</td>
<td>0.79</td>
<td>0</td>
<td>7</td>
</tr>
<tr>
<td>Age Founded</td>
<td>1807</td>
<td>39.65</td>
<td>10.59</td>
<td>18</td>
<td>83</td>
</tr>
<tr>
<td>Age Founded Squared</td>
<td>1807</td>
<td>1684.19</td>
<td>920.07</td>
<td>324</td>
<td>6889</td>
</tr>
<tr>
<td>Bachelor's degree</td>
<td>2000</td>
<td>0.43</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Master's Degree</td>
<td>2000</td>
<td>0.41</td>
<td>0.49</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Operating Years</td>
<td>1837</td>
<td>14.34</td>
<td>11.30</td>
<td>0</td>
<td>74</td>
</tr>
<tr>
<td>Industry</td>
<td>1600</td>
<td>9.77</td>
<td>4.34</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Number of Cofounders</td>
<td>2056</td>
<td>1.05</td>
<td>1.22</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>VC funded</td>
<td>1691</td>
<td>0.13</td>
<td>0.34</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Log initial capital</td>
<td>1264</td>
<td>11.91</td>
<td>2.72</td>
<td>0.28</td>
<td>21.02</td>
</tr>
<tr>
<td>Functional Diversity of Team</td>
<td>1964</td>
<td>1.23</td>
<td>0.48</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>
### TABLE 2 Productivity regressions

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>LN(REVENUES) (2-1)</th>
<th>PR(ACQUIRED) (2-2)</th>
<th>PR(IPO) (2-3)</th>
<th>LN(EMPL) (2-4)</th>
<th>LN(SURVIVAL) (2-5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cross Func. experiences</td>
<td>-0.269 (0.206)</td>
<td>0.040 (0.051)</td>
<td>0.002 (0.069)</td>
<td>0.066 (0.057)</td>
<td>-0.028* (0.016)</td>
</tr>
<tr>
<td>Num. prior acquired</td>
<td>0.121 (0.328)</td>
<td>0.396*** (0.087)</td>
<td>0.084 (0.116)</td>
<td>0.160 (0.103)</td>
<td>0.058 (0.024)</td>
</tr>
<tr>
<td>Num. same 2 digit SIC</td>
<td>0.396 (0.456)</td>
<td>-0.239* (0.125)</td>
<td>-0.014 (0.161)</td>
<td>0.442*** (0.143)</td>
<td>0.014 (0.034)</td>
</tr>
<tr>
<td>Age at founding year</td>
<td>0.025 (0.013)</td>
<td>-0.012*** (0.004)</td>
<td>0.001 (0.005)</td>
<td>-0.012*** (0.004)</td>
<td>0.006 (0.001)</td>
</tr>
<tr>
<td>Gender (1=male)</td>
<td>1.179*** (0.648)</td>
<td>0.404** (0.202)</td>
<td>0.372 (0.289)</td>
<td>0.582*** (0.153)</td>
<td>0.059 (0.052)</td>
</tr>
<tr>
<td>Masters</td>
<td>-0.237*** (0.287)</td>
<td>-0.016 (0.076)</td>
<td>0.170* (0.103)</td>
<td>0.305*** (0.086)</td>
<td>0.040 (0.028)</td>
</tr>
<tr>
<td>Doctorate</td>
<td>-0.183* (0.409)</td>
<td>-0.192* (0.102)</td>
<td>0.117 (0.130)</td>
<td>0.181 (0.121)</td>
<td>0.111 (0.036)</td>
</tr>
<tr>
<td>ln(emp)</td>
<td>1.752 (0.292)</td>
<td>0.055*** (0.019)</td>
<td>0.188*** (0.025)</td>
<td>0.535*** (0.074)</td>
<td>0.532*** (0.074)</td>
</tr>
<tr>
<td>ln(firm age)</td>
<td>0.539 (0.076)</td>
<td>0.173*** (0.057)</td>
<td>0.358*** (0.097)</td>
<td>0.532*** (0.074)</td>
<td>0.532*** (0.074)</td>
</tr>
<tr>
<td>MA</td>
<td>-0.546* (0.332)</td>
<td>0.330*** (0.081)</td>
<td>0.260*** (0.104)</td>
<td>0.214** (0.098)</td>
<td>-0.021 (0.030)</td>
</tr>
<tr>
<td>CA</td>
<td>-0.177 (0.346)</td>
<td>0.389*** (0.092)</td>
<td>0.440*** (0.123)</td>
<td>-0.030 (0.102)</td>
<td>0.010 (0.033)</td>
</tr>
<tr>
<td>Constant</td>
<td>-13.826 (3.467)</td>
<td>-1.422 (1.347)</td>
<td>-2.543*** (0.994)</td>
<td>-3.290*** (0.626)</td>
<td>1.412*** (0.198)</td>
</tr>
<tr>
<td>Year F.E.</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
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<tr>
<td>SIC F.E.</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
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<tr>
<td>Individual F.E.</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.2164</td>
<td>0.160</td>
<td>0.228</td>
<td>0.150</td>
<td>0.622</td>
</tr>
<tr>
<td>Num. of obs.</td>
<td>1294</td>
<td>1997</td>
<td>1760</td>
<td>2092</td>
<td>2217</td>
</tr>
</tbody>
</table>

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses.
**TABLE 3**

Major Industry Disruption

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Pr(Acquired)</th>
<th>Pr(Public)</th>
<th>Ln(empl)</th>
<th>Ln(Revenues)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(3-1)</td>
<td>(3-2)</td>
<td>(3-3)</td>
<td>(3-4)</td>
</tr>
<tr>
<td>Cross-functional Experience</td>
<td>0.281</td>
<td>0.277</td>
<td>0.760*</td>
<td>1.333**</td>
</tr>
<tr>
<td></td>
<td>(0.289)</td>
<td>(0.387)</td>
<td>(0.393)</td>
<td>(0.596)</td>
</tr>
<tr>
<td>Post-1997*Cross Func. Experience</td>
<td>-1.208**</td>
<td>-1.581*</td>
<td>-0.896</td>
<td>-0.302</td>
</tr>
<tr>
<td></td>
<td>(0.524)</td>
<td>(0.826)</td>
<td>(0.568)</td>
<td>(0.840)</td>
</tr>
<tr>
<td>Post-1997</td>
<td>0.532</td>
<td>1.089</td>
<td>-3.578</td>
<td>-7.316</td>
</tr>
<tr>
<td></td>
<td>(0.907)</td>
<td>(0.945)</td>
<td>(2.956)</td>
<td>(2.989)</td>
</tr>
<tr>
<td>Age founded</td>
<td>-0.0314**</td>
<td>-0.020</td>
<td>-0.0348**</td>
<td>-0.029</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.016)</td>
<td>(0.015)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Num. cofounders</td>
<td>0.180**</td>
<td>0.299**</td>
<td>0.442***</td>
<td>0.383**</td>
</tr>
<tr>
<td></td>
<td>(0.089)</td>
<td>(0.126)</td>
<td>(0.119)</td>
<td>(0.180)</td>
</tr>
<tr>
<td>Bachelor’s Degree</td>
<td>0.359</td>
<td>0.771</td>
<td>0.706</td>
<td>1.001</td>
</tr>
<tr>
<td></td>
<td>(0.367)</td>
<td>(0.600)</td>
<td>(0.441)</td>
<td>(0.637)</td>
</tr>
<tr>
<td>Master’s Degree</td>
<td>-0.003</td>
<td>0.218</td>
<td>0.949**</td>
<td>0.606</td>
</tr>
<tr>
<td></td>
<td>(0.375)</td>
<td>(0.624)</td>
<td>(0.447)</td>
<td>(0.662)</td>
</tr>
<tr>
<td>Log(initial capital)</td>
<td>0.128***</td>
<td>0.156**</td>
<td>0.288***</td>
<td>0.214**</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.065)</td>
<td>(0.057)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.327</td>
<td>-2.823**</td>
<td>1.796</td>
<td>16.370***</td>
</tr>
<tr>
<td></td>
<td>(1.172)</td>
<td>(1.262)</td>
<td>(3.004)</td>
<td>(2.767)</td>
</tr>
<tr>
<td>Founding Year F.E.</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>SIC F.E.</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.209</td>
<td>0.288</td>
<td>0.429</td>
<td>0.518</td>
</tr>
<tr>
<td>Observations</td>
<td>202</td>
<td>119</td>
<td>215</td>
<td>205</td>
</tr>
</tbody>
</table>

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Models 4-3 and 4-4 contain additional year fixed effects for the most recent operating year that revenues and employees were reported on.
TABLE 4 Productivity analysis including individual fixed effects

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>LN(REVENUES) (4-1)</th>
<th>PR(ACQUIRED) (4-2)</th>
<th>PR(IPO) (4-3)</th>
<th>LN(EMPLOYEES) (4-4)</th>
<th>LN(SURVIVAL) (4-5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cross-Func. experience</td>
<td>0.597 (0.551)</td>
<td>2.326*** (0.181)</td>
<td>-0.099 (0.074)</td>
<td>0.029 (0.129)</td>
<td>0.161*** (0.043)</td>
</tr>
<tr>
<td>Num. prior acquired</td>
<td>-0.028 (0.747)</td>
<td>-5.105*** (0.221)</td>
<td>0.331*** (0.114)</td>
<td>0.078 (0.186)</td>
<td>-0.119** (0.060)</td>
</tr>
<tr>
<td>Num. same 2 digit SIC</td>
<td>-0.573 (0.799)</td>
<td>-0.298 (0.248)</td>
<td>0.090 (0.154)</td>
<td>-0.034 (0.208)</td>
<td>0.010 (0.064)</td>
</tr>
<tr>
<td>Age at founding year</td>
<td>0.363** (0.160)</td>
<td>-0.103*** (0.010)</td>
<td>0.000 (0.005)</td>
<td>-0.016 (0.011)</td>
<td>0.013 (0.013)</td>
</tr>
<tr>
<td>ln(emp)</td>
<td>1.208*** (0.598)</td>
<td>-0.099** (0.045)</td>
<td>0.158*** (0.025)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln(firm age)</td>
<td>1.730** (0.482)</td>
<td>0.359** (0.157)</td>
<td>0.394*** (0.093)</td>
<td>0.322** (0.145)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-29.59*** (9.765)</td>
<td>-0.126*** (0.066)</td>
<td>-2.105** (0.959)</td>
<td>-0.643 (1.137)</td>
<td>3.683*** (0.496)</td>
</tr>
<tr>
<td>Year F.E.</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>SIC F.E.</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Individual F.E.</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.740</td>
<td>0.750</td>
<td>0.206</td>
<td>0.750</td>
<td>0.884</td>
</tr>
<tr>
<td>Num. of obs.</td>
<td>1528</td>
<td>463</td>
<td>1771</td>
<td>2135</td>
<td>2231</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model 5-1 (N=964)</th>
<th>Model 5-2 (N=964)</th>
<th>Model 5-3 (N=648)</th>
<th>Model 5-4 (N=964)</th>
<th>Model 5-5 (N=997)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Founder characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age at founding</td>
<td>-0.015*</td>
<td>-0.013</td>
<td>-0.019</td>
<td>-0.012</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.012)</td>
<td>(0.009)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Cross-functional Experiences</td>
<td>0.296***</td>
<td>--</td>
<td>--</td>
<td>--</td>
<td>0.119***</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td></td>
<td></td>
<td></td>
<td>(0.033)</td>
</tr>
<tr>
<td>Bachelor’s deg.</td>
<td>0.298</td>
<td>0.298</td>
<td>0.586+</td>
<td>0.346</td>
<td>-0.027</td>
</tr>
<tr>
<td></td>
<td>(0.254)</td>
<td>(0.256)</td>
<td>(0.335)</td>
<td>(0.255)</td>
<td>(0.132)</td>
</tr>
<tr>
<td>Master’s degree</td>
<td>0.402</td>
<td>0.402</td>
<td>0.508</td>
<td>0.434+</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>(0.252)</td>
<td>(0.255)</td>
<td>(0.334)</td>
<td>(0.254)</td>
<td>(0.132)</td>
</tr>
<tr>
<td>Characteristics of the Prior Exper.</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># Same State</td>
<td>0.238*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.096)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td># Different State</td>
<td>0.125</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>(0.104)</td>
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<td></td>
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<tr>
<td>Same 2 digit SIC</td>
<td>1.675**</td>
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<tr>
<td></td>
<td>(0.614)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Different 2 digit SIC</td>
<td>0.153</td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.623)</td>
<td></td>
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</tr>
<tr>
<td>Prior acquisitions</td>
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<td></td>
<td></td>
<td></td>
<td>0.445**</td>
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<td>Prior IPOs</td>
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<td>(0.341)</td>
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<td>Controls</td>
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</tr>
<tr>
<td>Functional Diversity of Founders</td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<td>(0.094)</td>
</tr>
<tr>
<td>Operating Years</td>
<td>0.059***</td>
<td>0.062***</td>
<td>0.073***</td>
<td>0.061***</td>
<td>0.041***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.017)</td>
<td>(0.022)</td>
<td>(0.017)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Initial Capital</td>
<td>0.395***</td>
<td>0.402***</td>
<td>0.368***</td>
<td>0.393***</td>
<td>0.181***</td>
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<tr>
<td></td>
<td>(0.035)</td>
<td>(0.036)</td>
<td>(0.047)</td>
<td>(0.036)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Used VC</td>
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<td>--</td>
<td>--</td>
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<tr>
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<td></td>
<td></td>
<td></td>
<td>0.343**</td>
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<td></td>
<td></td>
<td></td>
<td>(0.146)</td>
</tr>
<tr>
<td>Number of Cofounders</td>
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<td>0.249***</td>
<td>0.357***</td>
<td>0.256***</td>
<td>0.127***</td>
</tr>
<tr>
<td></td>
<td>(0.073)</td>
<td>(0.073)</td>
<td>(0.097)</td>
<td>(0.073)</td>
<td>(0.042)</td>
</tr>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Year dummies</td>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
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</tr>
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<td>12.247***</td>
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<td>8.989**</td>
<td>12.331</td>
<td>0.856</td>
</tr>
<tr>
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<td>(2.692)</td>
<td>(2.715)</td>
<td>(3.013)</td>
<td>(2.710)</td>
<td>(1.466)</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.353</td>
<td>0.291</td>
<td>0.362</td>
<td>0.346</td>
<td>0.330</td>
</tr>
</tbody>
</table>

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


References


March J, Simon H. 1958. Organizations. Wiley:


