On the Performance and Financing of Nascent Entrepreneurs

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ABSTRACT

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In this dissertation, three stand-alone studies are presented under a common theme: how do nascent entrepreneurs benefit from knowledge transfer? In the first study, I show that entrepreneurs reinforced their prudence by taking basic business training. Training reduced their financing, employment and business growth, but increased their profit. In the second study, entrepreneurs with high risk tolerance are found to operate larger businesses but suffer worse financial performance. Collectively, those two studies highlight the benefits of knowledge transfer in reinforcing discipline. The third study finds knowledge inherited from working at a prominent company helps entrepreneurs with managing their ventures. The benefits, however, diminish if the entrepreneurs deviate from the line of business that they used to work in.

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At a more personal level, I am indebted to my family. Their entrepreneurial experience not only inspires my research, but also imparts on me the courage and prudence to weather the vicissitude of life.

Chapter 1

Overview

This dissertation consists of three stand-alone articles that share a common theme: How nascent entrepreneurs benefit from knowledge transfer? In these articles, nascent entrepreneurs refer to individuals engaging in the process of starting a business venture. For many of those individuals, entrepreneurship is a source of household income and subjective utility; for the societies, entrepreneurship is a source of employment and innovation. It is perhaps not surprising that policy makers lend substantial support to entrepreneurs. Of the two largest economies in the world, the U.S. administration signed into law the Jumpstart Our Business Startups (JOBS) Act setting aside 12 billion dollars as loan support for small businesses,[1] and the Chinese administration recently announced a series of measures to promote entrepreneurship, including tax breaks, loan guarantees and social security subsidies.[2] In its recent annual report, the Chinese State Council explicitly upheld "mass entrepreneurship and innovation" as a strategy to cope with the slowing economic growth.[3]

Despite the attention and recent environmental munificence, starting a business remains inherently adventuous for the nascent entrepreneurs, in the sense that the individuals are bounded by limited resources and face uncertainty about their ability and the market. Whereas a few rising

[1] U.S. Small Business Administration (2010a)

[2] http://www.bloomberg.com/news/articles/2015-05-01/china-promotes-startups-to-boost-job-creation-as-economy-slows. Accessed on August 10th, 2015.

[3] http://news.xinhuanet.com/english/2015-03/11/c_134059020.htm. Accessed on August 10th, 2015.

stars are frequrently featured in the media, the vast majority of startups have difficulty attracting sufficient financial capital to grow—data from the internet startup universe show that only less than a quarter of nascent businesses were able to secure external funding.[4] In this dissertation, I aim to shed light on what drives the financing and performance of nascent entrepreneurs and what they can do to improve. Specifically, I investigate the following question: Do nascent entrepreneurs benefit from knowledge transfer, and if so, how? The three stand-alone articles, presented respectively in the three chapters below, provide answers using data from different contexts.

In Chapter 2, I study whether entrepreneurs can do better by receiving basic business training, and if so, what is the most useful for them to learn. I draw on data from a U.S. government program which provided training to randomly selected individuals interested in pursuing entrepreneurship. To identify the primary mechanism whereby the training affected the entrerpeneurs, I develop an empirical strategy that uses the differential predictions on capital investment. The results suggest that basic business training helped to increase profit. It did not improve efficiency, but rather reinforced entrepreneurs' prudence in decision making. By receiving training, entrepreneurs tended to raise less capital, hired fewer employees and grew their businesses more slowly.

Chapter 3 echos the importance of prudence, but focuses on the performance implications of one personality trait—the entrepreneurs' risk propensity. Using a novel dataset of Chinese households, I show that households guided by more risk-tolerant individuals are more likely to enter into entrepreneurship. I further show that entrepreneurs' risk propensity is generally not a strong predictor of their performance, except that the very risk tolerant ones tended to operate larger business but had lower revenue and lower profit. To disentangle the effects of risk propensity from overconfidence, I then conducted an experiment where both personality traits were explicitly measured. The effects of risk propensity are robust even after the individuals' level of confidence is controlled for.

Chapter 4 examines whether knowledge transfer from former employers benefits entrepreneurs. In the literature, spawns, or ventures started by former employees at a prominent employer, have

[4]See Table 4.2 in Chapter 4 for details.

been shown to enjoy greater likelihood of success. However, it remains unclear whether this is due to selection on the labor market or inherited human/social capital. It is also not clear what entrepreneurial abilities prominent companies help to develop. This chapter draws on a sample of U.S. technology startups, and finds that working for a prominent company helps prepare entrepreneurs with managing their new ventures. However, the benefits exist for only new ventures operating in a line of business similar to their founders' former employers'.

Collectively, the three articles suggest that entrepreneurs benefit from knowledge transfer, in ways that differ by the context and also the substance of the knowledge. Knowledge may reinforces entrepreneurs' discipline. Their financial performance benefits from a maintaining a balance between passion and prudence. In deciding whether to pursue an opportunity, entrepreneurs are advised to take on a more realistic perspective and better self-control. Inherited knowledge from former employment may also prepares entrepreneurs with better business management, to the extent that their new ventures' business is not too far from their former employers.

Chapter 2

Knowledge is Prudence: How Entrepreneurs Benefit from Business Training in a Field Experiment[1]

Abstract

Can entrepreneurship be learned, and if so, what is most useful for entrepreneurs to learn? These issues have been difficult to address because of the endogeneity of learning and the lack of an empirical strategy to unpack how it affects entrepreneurs. Using data from a field experiment where free entrepreneurship training was randomly distributed, I show that entrepreneurs effectively improved their financial performance by participating in training. To identify the primary mechanism

[1]I thank Aseem Kaul, Bruce Kogut, Mattia Landoni, Jiao Luo, Stephan Meier, Damon Phillips, Andrea Prat, Evan Rawley, David Ross, Robert Seamans and Scott Stern for helpful comments. Special thanks to Jacob Benus, Robert Fairlie and Jonathan Simonetta for clarifications on the the GATE data. I am also grateful to the participants of the Atlanta Comparative Advantage Conference, the Consortium on Competitiveness and Cooperation, the NYU-Columbia Doctoral Conference and the Trans-Atlantic Doctoral Conference. Glamis Haro, Lawrence King, Natalie Moses and Kaaryn Simmons at the Small Business Administration provided valuable insights on the practice of business training. All errors are mine.

for this effect, I exploit the different predictions of how training affects capital investment. Interestingly, the improvement did not seem to be driven by increased production efficiency, but rather by entrepreneurs learning to refine their business ideas and thus reducing excessive investment. As a result of learning, they invested less in business, hired fewer employees and grew their businesses more slowly, but achieved better performance. This paper contributes a novel strategy for unpacking the benefits of learning, and also provides a demand-side perspective for addressing entrepreneurs' resource constraints.

"The entrepreneurial mystique? It's not magic, it's not mysterious, . . . It's a discipline. And, like any discipline, it can be learned."

—Peter Drucker[2]

"The real discipline comes in saying no to the wrong opportunities."

—Peter Drucker[3]

2.1 Introduction

Can entrepreneurship be learned? And for many pursuing an entrepreneurial career, it remains unclear as to what is most useful for them to learn: is it the specific know-hows to increase competence, such as how to manage employees, or is it the more general ability for business planning? As much as they are important for both the entrepreneurs and the broader economy, these issues have been difficult to address not only because learning is endogenous, but also because of the lack of an empirical strategy to unpack how it affects entrepreneurs.

This paper is aimed to fill this gap. Specifically, I study entrepreneurs' learning in the context of a field experiment where basic business training was randomly distributed. My research question is: How do entrepreneurs benefit from entrepreneurship training? I break down this question into two parts that are empirically testable: 1) Can entrepreneurs improve their performance by participating in training? 2) If so, what is the primary mechanism? By identifying the primary mechansim, we can then understand what from the training contributes the most to their improvement (if any).

Theoretically, the literature proposes two potential mechanisms whereby entrepreneurship training may affect performance. The two mechanisms differ in whether training affects how good the business *actually* is, or training affects how good the entrepreneur *thinks* her business is. The

[2]Drucker (1985).
[3]Boorstin (2005).

first is the "productivity" mechanism: training adds to entrepreneurs' human capital, making it more profitable to expand the production scale. It follows that business training improves financial performance and increases entrepreneurs' capital investment in production. The second is the "prudence" mechanism: entrepreneurs may not have an accurate assessment of their business. In particular, they are subject to the overconfidence bias. Training refines entrepreneurs' business ideas*, i.e.*, it helps to scale down excessive investment. In this case, training improves performance by preventing financial loss, and decreases entrepreneurs' capital investment.

To illustrate the two mechanisms, consider an example of the common business analytical tools such as the SWOT matrix.[4] Knowledge of those tools may help entrepreneurs to identify their strengths and new opportunities, thus motivating them to expand production in order to capture more market shares. It may also alert them to their weaknesses and potential threats, thus reducing capital investment inspired by unrealistic expectations. In a training program, both mechanisms may be in effect. This paper is aimed to identify the dominating one.

To empirically answer the research question, I draw on data from a training program titled "Growing America through Entrepreneurship (GATE)". The program was designed as a field experiment, where free training conducted by professionals was randomly granted to the applicants. The training taught basic business skills, as well as provided counseling for starting and managing a small business. This experimental design is valuable for identifying the causal effects, because receiving training is an endogenous decision by the individuals. My overall strategy consists of four pieces of analyses. To investigate the issue of "whether entrepreneurs can improve performance by taking training", Analysis 1 focuses on the average monthly profit. Targeting the issue of "primary mechanism", my strategy considers both action- and opinion-based evidence. First, I exploit the different predictions by the two mechanisms on capital investment. Analysis 2 proxies capital investment by its antecedent—financing, and Analysis 3 proxies by its outcome—production scale and its growth (both measured by employment). Second, through surveying and in-person interviewing, Analysis 4 presents opinions from both trainees and trainers regarding how receiving

[4]SWOT stands for "strength, weakness, opportunity and threat." See Pickton and Wright (1998) for an introduction to the SWOT matrix.

training helps entrepreneurs.

The results support prudence as the primary mechanism: by taking business training, entrepreneurs mainly learn to mitigate overconfidence, which translates into better performance. Analysis 1 finds that taking training improves financial performance, and the effect concentrates on loss prevention—receiving training lowers the likelihood of operating loss, but has little impact on the right tail of the earnings distribution. The results of the other anlayses suggest that "prudence" is the primary mechanism. First, training reduces entrepreneurs' capital investment in production. Analysis 2 finds that receiving training decreased the business financing. Analysis 3 shows that the entrepreneurs with more training had smaller production scale and slower business growth. Second, as Analysis 4 documents, the individuals reported "refining business ideas" as a major way that training helped them. And the prudence mechanism was also confirmed by two trainers at a sponsoring institution of GATE. In essence, the learning helped the average entrepreneur by substituting for some possibility of "financial loss from overconfidence-driven investment" with the possibility of "higher performance based on reasonable planning".

Furthermore, I conduct three sets of robustness checks on the empirical results. First, I use weighted regressions to show that the empirical findings are not driven by differential sample attrition. Second, I show that the results are robust to alternative sampling strategies. Third, based on additional statistical evidence, I find little evidence for training improving the entrepreneurs' production efficiency. In other words, it does not seem to be the case that entrepreneurs can effectively learn to increase efficiency by taking training.

Overall, this paper highlights improved cognitive ability as the primary contributor to the benefits of entrepreneurs' learning, and thus suggests that it is most useful for entrepreneurs to learn skills or knowledge, such as business planning tools, that mitigate overconfidence and foster prudence.

This paper contributes an innovative strategy to unpack the mechanims of entrepreneurs' learning. By doing so, it provides the first answer to the question of what is most useful for entrepreneurs to learn. The answer sheds light on how to improve the quality of entrepreneurship. This not only has implications for individuals, but also helps policy makers to design better training programs (McKenzie and Woodruff, 2012).

By identifying prudence as the primary mechanism, this paper also contributes to an ongoing debate in the literature on new venture strategy. Previous research argues that "nascent entrepreneurs should aggressively pursue opportunities in the short-term"(Carter et al., 1996). To counter that argument, some studies highlight the benefits of business planning (e.g. Delmar and Shane (2003)), but none has directly shown that being less aggressive contributes to nascent entrepreneurship. This paper fills this gap. In contrast to aggressive investment, the results suggest that smaller scale and slower growth may represent a more sustainable strategy for new ventures.

2.2 Two Theories, Different Predictions

Drawing on two strands of related literature, I develop the theoretical predictions of how receiving business training affects entrepreneurs' performance. As detailed below, the theories generally agree on the effect on the performance, but disagree on the mechanism. The disagreement is rooted in the assumption of whether entrepreneurs have the cognitive ability to accurately assess themselves and the environment (Simon, 1955). Each strand of the literature contributes a potential mechanism, which I term "productivity" and "prudence" respectively.

In this section, I use a simple formal model to illustrate the two mechanisms and derive the propositions. The model is based on the original work by Stein (2003) and consists of a single agent (entrepreneur) and two stages. At stage 1, the entrepreneur invests amount I of financial capital into business production. She has endowment W and needs to borrow $\max[I-W,0]$. At stage 2, the investment yields financial return $m \cdot I^{\alpha}$ where $\alpha \in (0,1)$ denotes the diminishing return to investment and $m > 0$ denotes the actual managerial capability of the entrepreneur (Evans and Jovanovic, 1989).

The agent aims to maximize the net present value of the actual return to entrepreneurship:

$$\pi_A(I) \equiv \frac{m \cdot I^\alpha}{1+r} - I - C(\max[I-W, 0])$$

where $r > 0$ is the risk-adjusted interest rate and $C(\cdot)$ is the cost of using debt financing. Naturally, $C(0) = 0$. We also assume $C'(\cdot) > 0$ and $C''(\cdot) \geq 0$ to reflect the positive and non-decreasing marginal cost of debt financing.[5]

2.2.1 The Productivity Mechanism

From the perspective of neoclassical economics, human beings are "rational"—they are able to access complete information for making the optimal decision.[6] In this sense, rational entrepreneurs possess accurate knowledge of themselves and the environment, and optimize their behavior according to such accurate knowledge. Learning benefits them mainly through increasing the production efficiency, as defined by the marginal return to the production factors (e.g. labor or equipment). As a result, other things constant, entrepreneurs with training can obtain greater financial gains from employing the same amount of production factors than those without training (e.g. Lucas (1978); Evans and Jovanovic (1989)). For example, better management skills or better marketing strategies may increase the revenue per unit of labor.

Specifically, training may improve production efficiency in two ways. First, it facilitates the adoption of know-hows. The know-hows add to the entrepreneur's human capital, thereby strengthening the business competence (Coff, 1997). The strengthened competence makes entrepreneurs capable of capturing greater market shares, and motivates them to expand production. This is particularly the case for businesses at a growing stage. For example, Bloom et al. (2013) find that professional consultancy boosts factory productivity by 17 percent on average, and results in more plant openings. Similarly, Ichniowski and Shaw (1999) show that adopting innovative practices

[5] A more general form of the utility function would be a weighted sum of the financial return and a constant term denoting the subjective utility from being an entrepreneur. The analytical results are not sensitive to this variation.

[6] This perspective is also termed more generally as "rational choice theory".

of human resource management significantly improves productivity. At an aggregate level, countries experiencing productivity growth tend to accumulate savings to finance more entrepreneurial investment (Sandri, 2014). Second, training streamlines the exploitation of market opportunities. That is, knowledge transfer expedites collecting and processing the information needed to exploit new opportunities. For example, entrepreneurs with more exposure to knowledge of doing business abroad are more likely to export (Filatotchev et al., 2009). New market opportunties expand the demand for the product, thus lifting the marginal return to production factors.

In sum, training makes it more profitable for entrepreneurs to expand their production. In the model, under the assumption of accurate knowledge, the entrepreneur aims to decide on the amount of investment to maximize the actual return

$$\max_{I} \pi_A(I).$$

Let I_A be the investment amount that maximizes π_A. Receiving training increases m. Then, the model informs the following based on neoclassical economics:

Proposition 1. ***(the Productivity Mechanism):*** $\partial[\pi_A(I_A)]/\partial m > 0$ ***and*** $\partial I_A/\partial m > 0$***, i.e., receiving business training improves financial performance, and increases entrepreneurs' capital investment in their businesses.***[7]

2.2.2 The Prudence Mechanism

Drawing on insights from economics and social psychology, the behavioral decision theory emphasizes the role of entrepreneurs' cognitive ability in their decision making (Slovic et al., 1977; Simon, 1972). This theory relaxes the assumption of perfect rationality, and instead argues that human beings are only partially (or "boundedly") rational due to cognitive limitations. This implies that entrepreneurs tend to make decisions under incomplete information. This is particularly true of nascent entrepreneurs due to two reasons. First, a comprehensive set of information is either

[7] See Appendix I for proof.

unavailable or too costly to gather. On the contrary, heuristics based on information sourced from personal experience or observation provides a less costly solution (Tversky and Kahneman, 1974). Second, nascent businesses typically do not have established routines that can serve as guidance (Nelson and Winter, 1982; Kogut and Zander, 1992).

The most widely and consistently documented cognitive limitation is overconfidence. Overconfidence is broadly defined in the literature as the tendency to: 1) overestimate the expected return to a project; or 2) underestimate the variance (risk) of the return to a project (Åstebro et al., 2014). Overconfidence is a stylized fact about entrepreneurs in a longstanding stream of literature (e.g. Busenitz and Barney (1997); Simon and Houghton (2002); Hayward et al. (2006); Koellinger et al. (2007); Pirinsky (2013)). Many enter entrepreneurship because they perceive the return to be more favorable than those who do not enter. In general, entrepreneurs tend to overestimate their skills and the odds of business success (Cooper et al., 1988; de Meza and Southey, 1996; Wu and Knott, 2006). Compared with corporate employees, they are more likely to be subject to "wishful thinking" of better financial outcomes but tend to have worse actual performance (Arabsheibani et al., 2000).

Overconfidence has implications for entrepreneurs' investment and performance. First, it leads to excessive capital investment. This may result from overestimating the demand for own products and underestimating customers' likelihood of switching to competitors (Mahajan, 1992; Camerer and Lovallo, 1999; Malmendier and Tate, 2005), or understimating the cost of carrying out a project (Baron, 1998). Second, as overconfidence translates into unrealistic goals and misguided investment, it causes failures of individual projects as well as harms entrepreneurs' performance in general (Koellinger et al., 2007; Hmieleski and Baron, 2009). For example, Simon and Houghton (2003) show that overconfident entrepreneurs feel more optimistic about their products' prospect, release more risky products but are less likely to succeed with their release. The performance implications of overconfidence are gravely summarized in Barnes (1984), "Unfortunately, overconfidence may cause the strategic planner to overlook or misjudge pathways to disaster." In practice, investors are concerned about the negative consequences that arise from entrepreneurs' overconfidence. Some venture capitalists even went so far as to devise psychometric test on entrepreneurs to separate the "completely delusional" from the slightly overconfident.[8]

Business training mitigates entrepreneurs' overconfidence. The knowledge of analytical tools and the information exchange helps entrepreneurs to form a more realistic picture of their businesses and cut the excessive investment (Mahajan, 1992). This way, training essentially accelerates the entrepreneurs' learning about themselves and their businesses (Jovanovic, 1982).

In the model, the behavioral decision theory argues that the entrepreneur may not perceive the actual return function $\pi_A(I)$. Instead, due to cognitive limitations, the entrepreneur perceives the following payoff function:

$$\pi_P(I) \equiv \frac{(1+\tau)\cdot m \cdot I^{\alpha}}{1+r} - I - C(\max[I-W,0])$$

where$\tau \geq 0$ is her degree of misperception of the investment return (Ben-David et al., 2013). A larger value of τ indicates a higher level of overconfidence,[9] and receiving training reduces τ. In deciding on the amount of investment, the entrepreneur aims to maximize the perceived return:

$$\max_{I} \pi_P(I).$$

Let I_P be the investment amount that maximizes π_P. The entrepreneurs invests I_P and receives $\pi_A(I_P)$ in actual return. The model informs the following based on behavioral decision theory:

Proposition 2. ***(the Prudence Mechanism):*** $\partial[\pi_A(I_P)]/\partial\tau < 0$ ***and*** $\partial I_P/\partial\tau > 0$***, i.e., receiving business training improves financial performance, and decreases entrepreneurs' capital investment in their businesses.***[10]

As a side note on the two propositions above, both mechanisms may possibly be in effect, and the primary mechanism is likely to vary across individuals. For instance, those with better cogntive

[8]http://www.economist.com/news/business/21618816-instead-romanticising-entrepreneurs-people-should-understand-how-hard-their-lives-can (accessed Oct 10, 2014).

[9]The productivity mechanism is essentially a special case with $\tau = 0$. In that case, $\pi_A(I) = \pi_P(I)$ for any $I \geq 0$.

[10]See Appendix I for proof.

abilities may benefit more through the productivity than the prudence mechanism. The goal of this paper, however, is to identify the effect and its primary mechanism for the average entrepreneur in the given empirical context.

2.3 Data and Empirical Strategy

The empirical analysis of this paper draws on data from a experiment where free entrepreneurship training was randomly distributed. The randomization is crucial for identifying the causal effect of training. This is because factors that are unobserved by the researchers may affect both the receipt of training and the outcome measures. Without randomization, causal inference is difficult because the effect of training could possibly be confounded with the effect of those unobserved factors. An example of such factors is entrepreneurs' motivation, which is often unobserved and positively influences both the training and the performance. Analyses that fail to account for the unobserved motivation would overestimate the causal effect of training on performance.

The experiment started in the year 2003. The Department of Labor (DOL) and the Small Business Administration (SBA), in a joint effort with local organizations, launched a program titled "Growing America through Entrepreneurship" (GATE) in three states (Benus et al., 2009).[11] The program was aimed to upgrade the business knowledge of those interested in enhancing their entrepreneurial career. Compared with the handful of other government-sponsored entrepreneurship training programs in the U.S., GATE remains the most comprehensive to date, in that its admission was not restricted to the unemployed and it was more diverse geographically and demographically (Benus et al., 2009). The comprehensivenss and the randomization make GATE an attractive setting for causal inference with a high level of generalizability. Recently, several studies have used the GATE sample. See Appendix II for a summary and how this paper differs from them.[12]

GATE was advertised extensively both by media and at DOL-affiliated institutions to reach a

[11] The locations include Philadelphia and Pittsburg of Pennsylvania, Minneapolis/St. Paul and Duluth of Minnesota, and Bangor, Portland and Lewiston of Maine. They reflect a balance between urban and rural demographies.

[12] The GATE dataset and surveys are available at http://www.doleta.gov/reports/projectgate (accessed Oct 8, 2014).

broad audience. In order to participate in GATE, people first registered through one of the multiple channels including phone, mail, internet and local One-Stop Career Centers. They then were asked to attend an orientation session at a local One-Stop Career Center, where a video introducing the program was shown. A nine-page application form was distributed to each attendee after the session was completed. The form asked each applicant to describe the idea of their current business or the one that they were about to start. On the last page of the application form and right before the applicant's signature, a note explicitly informed the applicant that admission to GATE would be decided by a random lottery due to space constraints. Completing and submitting the form by mail concluded the application process. Anyone aged 18 or above, legally authorized to work in the U.S., and with an appropriate business idea was eligible for GATE participation (Benus et al., 2009).

GATE received around 4,000 complete applications. The applicants were randomly assigned to one of two groups of roughly equal size. The control group did not receive any services from GATE, but was free to seek training at their own expense. In contrast, the treatment group was offered the option of free training by professional business consultants. The breadth of the training spanned across basic accounting, finance, marketing, legal issues and commerce-related information technology. In addition to lectures, one-on-one counseling sessions and peer group meetings were also available. After the random assignment, the treatment group members initiated their training by meeting a business consultant. Based on the assessment of the members' capability and needs, the consultant advised on the content of a personalized training plan. The average cost of training per treatment group member is estimated to be around $1,000 (Benus et al., 2009).

Both groups were followed up with three waves of telephone surveys about 6, 18 and 60 months respectively after the random group assignment. In this paper, I timestamp the group assignment as month 0. Then the three waves of surveys took place at respectively months 6, 18 and 60. The three waves asked a similar set of questions mainly concerning the individuals' training and businesses. This paper focuses on the information from the last wave (at month 60) to let the effects of training materialize more fully—In fact, 27.3 percent of the sample continued to attend classes or one-on-one counseling after the second wave (month 18); and of the 1,682 individuals that reported no entrepreneurial activities in the second survey, 299 (17.8 percent) of them entered entrepreneurship afterwards.

2.3.1 Empirical Strategy

I conduct four pieces of analyses to address the research question. In Analysis 1, I address the issue of "whether entrepreneurs can improve performance by taking training" by focusing on the average monthly profit. My strategy for addressing the issue of "primary mechanism" considers both action- and opinion-based evidence. For action-based evidence, I exploit the different predictions of the effect on capital investment. As the GATE sample does not report direct measures of capital investment, I use two sets of proxies. In Analysis 2, I proxy capital investment by its antecedent—financing. For nascent businesses, their capital investment in business production generally equal their financing because they rarely invest in non-production-related venues (e.g. financial securities). I further break down the start-up capital to debt and entrepreneurs' own money. In Analysis 3, I proxy capital investment by its outcome—business scale and growth rate, both measured in terms of the number of employees. For opinion-based evidence, Analysis 4 studies both the trainees and the trainers: First, on a Likert scale, the trainees reported how much training helped them with respect to a list of issues; Second, outside the context of GATE, I interviewed two trainers at the SBA, regarding the common issues that they help entrepreneurs to address.

Model For each of Analyses 1-3, I specify two classes of regression models. The first class of models estimate the average intent-to-treat (ITT) effects. They are specified as follows:

$$\mathbf{E}(y_i|Treat_i, \mathbf{X_i}) = f(\alpha + \gamma \cdot Treat_i + \mathbf{X_i}^\top \cdot \beta)$$

where the functional form $f(\cdot)$ may refer to Ordinary Least Squares (OLS), Logistic, Negative Binomial models etc. i is the individual indicator. y is the dependent variable of interest. $Treat$ is a binary indicator for being assigned to the treatment group. $\mathbf{X}$ is a vector of control variables reported at application, including the demographics and location fixed effects. The demographics include sex, race, age, years of education, marital status, disability status, whether i was born in U.S., whether i had children in household, years of self-employment experience, whether i worked for self-employed relatives or friends, whether i was receiving unemployment insurance benefits, preferences for risk and for autonomy,[13] and family income fixed effects.[14] The coefficient of main interest, γ, captures the ITT effect.

However, the ITT effects are not equivalent to the marginal effects of training, in that not all members of the treatment group received training and some of the control group members sought training at their own effort (as will be shown below). To directly estimate the marginal effects, I specify the second class of models: the local average treatment effects (LATE) models (Imbens and Angrist, 1994). They are essentially two-stage instrumental variable models:

$$Train_i = \eta + \theta \cdot Treat_i + \mathbf{X_i}^\top \cdot \psi + \mu_i$$
$$y_i = \alpha + \gamma \cdot \widehat{Train_i} + \mathbf{X_i}^\top \cdot \beta + \varepsilon_i$$

where $Train$ is the total number of hours that individual i spent in participating in business training. In this paper, I define "receiving business training" as attending workshops or one-on-one counseling sessions (Fairlie et al., 2012). Here I use the time spent on receiving training to represent the intensity of treatment. The rationale is that the longer one spends on training, the more useful information she gets, and thus the stronger the treatment effect.[15] The other variables are as speci-

[13]Following Fairlie and Holleran (2012), the individuals' preferences for risk and for autonomy are represented by respective indices. The risk tolerance index is constructed from the response to two psychometric statements in the application form. The statements are “I am only willing to take a risk if I am sure everything will work out." and “I am not prepared to risk my savings for my business." The applicants assess the extent to which each statement applies to themselves, and respond with an integer score between 1 and 5 with 1 being “very true" and 5 being “ very untrue". The two scores are normalized and averaged into one measure for risk tolerance. The autonomy index is contructed from the (reversely coded) response to the statement "I enjoy working independently." The two indices are also used in Fairlie et al. (2012).

[14]I cannot include industry fixed effects, becasue the GATE dataset does not contain information on the industry of the businesses started after the random group assignment. However, training rarely changes an entrepreneur's choice of industry. According to an experienced professional business trainer, Glamis Haro (introduced in Section 2.7), the likelihood of training causing industry change is about "one in a hundred cases".

[15]Alternatively, I define $Train$ as a binary indicator of whether the individual received any training. The LATE results are qualitatively similar, and are available upon request.

fied in the ITT model. At the first stage, $Train$ is instrumented by $Treat$ and the control variables. Its predicted value, $\widehat{Train}$, enters the second stage as the independent variable. The exclusion restriction criterion is satisfied because the group assignment was randomized. The coefficient γ captures the average treatment effect for entrepreneurs whose receipt of training is sensitive to the subsidy.[16]

Sample The statisical analyses are conducted on three samples. The first is based on the original sample from the last wave of survey (at month 60). It consists of each entrepreneur' most recent business, with "entrepreneurs" defined empirically as business owners. This is the default sample for analyses in the main text. In the survey, business-related information was recorded only if the respondent reported that she had business ownership experience since the previous survey (at month 18). If an individual had no such experience since month 18, she would not entrer this sample. Therefore, the first sample is a sample of the entrepreneurs' *most recent business since month 18*.

Whereas it seems natural to employ the original sample in the survey (Benus et al., 2009), the sampling strategy above invites two issues. One issue is that it leaves out entrepreneurs whose most recent business closed by month 18, potentially resulting in survivorship bias. To address this issue, I run the regressions using the second sample, which consists of the entrepreneurs' *most recent business since the random group assignment (at month 0)*. In this sample, if an individual had not been a business owner since month 18 but had been so prior to that, I include her most recent business. If an individual had not been a business owner since the random assignment, then she would not enter this sample.

The second issue is that business owners is only a subset of the full sample. Whereas the the full sample was randomly assigned to the groups, this is not necessarily the case for its subsets. To make causal inference using the first two samples, we need to assume that the business owners' unobserved attributes are identically distributed between the two groups.[17] To relax this

[16]Here I specify linear probability for the second stage of the LATE model. This allows us to directly interpret the marginal effects from the coefficient estimates. Alternatively, I also specify probit model for the second stage. The results remain qualitatively similar, and are available upon request.

[17]In support of this assumption, I show below that an identical share of each group had business ownership, that

assumption, I run the regressions using the third sample, which is the full sample consisting of *all individuals regardless of their entrepreneurial activities*. It builds on the second sample and codes the business-related variables as 0 for those without business-ownership experience since the random assignment. The regression results using the second and third samples are presented in the robustness checks.

2.3.2 Sample Overview

Table 2.1 summarizes the demographic profile that was reported at application. As consistent with the randomized design of the experiment, both the treatment and control groups shared very similar characteristics overall. Panel (a) summarizes the full sample at application. Females accounted for slightly less than half of each group. Blacks and Whites respectively made up 30 and 55 percent. On average, the participants were around 42 years of age[18] and had received 14 years of education. About 35 percent of them had family income of less than \$25,000. And 50 percent had annual family income between \$25,000 and \$75,000. About one fifth of each group was already operating their businesses at the time of application. Of these people, the industry distribution (untabulated) of their most recent businesses exhibited much diversity. The most popular industry was professional or technological services (accounting for about 20 percent), followed by retail trade and construction (each with a share of about 10 percent).

In the last wave of survey (month 60), the treatment and the control groups continued to share similar demographic configuration in the full sample (Panel (b)). Both groups also had almost identical shares of individuals with entrepreneurial experience. Of the full sample, about half had worked on entrepreneurship since month 18, and slightly over 60 percent had done so since the random group assignment.

In Panel (c), the individuals with recent entrepreneurial experience in both groups are demo-

the business owners were observationally very similar between the two groups, and that the inter-group difference in investment is unlikely due to selection. See Section 2.8.2 for details.

[18] The mean difference between the two groups is small (0.7 years). The statistical significance is likely due to "type I error" of hypothesis testing, that is, true non-difference producing a small p-value by chance.

graphically similar, and spent about the same amount of time (38 hours per week) working on their businesses.[19] Their businesses also shared similar lengths of operation. Compared with the full sample, the subsample of entrepreneurs features slightly fewer Black and more White people, and also fewer individuals with lower family income.

In addition, in terms of demographics, the GATE sample is similar to the nationally representative datasets of U.S. entrepreneurs (e.g. see Table I.1 of Benus et al. (2009) for a comparison with the Panel Study of Entrepreneurial Dynamics (PSED) dataset). In terms of business characteristics, the GATE sample demonstrates similar distributions to those of the Survey of Business Owners (SBO) administered by the U.S. government (e.g. see Table 5 of Fairlie et al. (2012)). This lends strength to the generalizability of the results in this paper.

Table 2.2 summarizes the training received by the entrepreneurs. The treatment group received substantially more training than the control group at both the extensive and intensive margins. 93 percent of the treatment group received training since the random group assignment, compared with only 77 percent of the control group. On average, the treatment group members received 35 hours of training, compared with 27 hours for the control group. The comparisons are similar if we break down training to workshops and one-on-one counseling sessions.

Training seemed to have cultivated business planning. As the table shows, 75 percent of the treatment group had developed a business plan, compared with 67 percent of the control group. This is consistent with the findings from other entrepreneurship training programs (Hiatt and Sine, 2014).

2.4 Analysis 1: Financial Performance

In Analysis 1, I show that entrepreneurs improved their financial performance by taking training. This is consistent with the prediction of both propositions. A closer scrutiny suggests that the

[19]The finding that both groups spent similar amount of time on entrepreneurship mitigates the concern for the Hawthorne effect. The Hawthorne effect implies that the treatment group would be more motivated and spend more time on startup activities.

Table 2.1: Participants' Characteristics Reported at Application

(a) Full Sample at Application

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Binary Indicators:							
Female	0.472	0.499	2094	0.457	0.498	2103	0.319
Black	0.305	0.460	2094	0.306	0.461	2102	0.905
White	0.552	0.497	2094	0.555	0.497	2102	0.814
Family Income < $25,000	0.363	0.481	2080	0.348	0.477	2090	0.323
Family Income $25,000-75,000	0.506	0.500	2080	0.510	0.500	2090	0.806
Business Owner	0.183	0.387	2046	0.195	0.396	2045	0.334
Continuous Measures:							
Age (Years)	42.076	10.197	2092	42.772	10.211	2101	0.028
Education (Years)	14.389	2.208	2094	14.515	2.240	2103	0.067

(b) Full Sample in Last Survey (Month 60)

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Binary Indicators:							
Female	0.481	0.500	1274	0.471	0.499	1176	0.618
Black	0.253	0.435	1274	0.260	0.439	1175	0.699
White	0.625	0.484	1274	0.628	0.484	1175	0.867
Family Income < $25,000	0.310	0.463	1268	0.320	0.467	1169	0.596
Family Income $25,000-75,000	0.521	0.500	1268	0.517	0.500	1169	0.850
Worked on Entrepreneurship							
Since Month 18	0.489	0.500	1274	0.491	0.500	1176	0.902
Since Random Assignment	0.639	0.480	1274	0.628	0.484	1176	0.559
Continuous Measures:							
Age (Years)	43.912	9.906	1272	44.157	9.980	1175	0.544
Education (Years)	14.751	2.153	1274	14.777	2.191	1176	0.767

(c) Sample with Business Ownership since Month 18

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Binary Indicators:							
Female	0.443	0.497	623	0.472	0.500	578	0.309
Black	0.205	0.404	623	0.215	0.411	578	0.700
White	0.669	0.471	623	0.680	0.467	578	0.696
Family Income < $25,000	0.266	0.442	620	0.297	0.458	575	0.230
Family Income $25,000-75,000	0.526	0.500	620	0.508	0.500	575	0.535
Continuous Measures:							
Age (Years)	43.743	9.829	622	44.163	9.781	578	0.459
Education (Years)	15.056	2.045	623	14.993	2.115	578	0.599
Weekly Hours on Entrepreneurship	37.755	25.682	609	37.977	27.188	568	0.886
Business Age (Years)	61.491	62.926	570	61.086	60.915	509	0.915

Table 2.2: Training Received by Entrepreneurs since Random Assigment

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Binary Indicators:							
Received Any Training	0.929	0.256	623	0.765	0.425	578	0.000
Attended Any Workshop	0.831	0.375	623	0.696	0.461	578	0.000
Attended Any Counseling	0.709	0.454	623	0.443	0.497	578	0.000
Developed Any Business Plan	0.751	0.433	623	0.671	0.470	578	0.002
Number of Hours Spent on:							
Training	35.136	48.242	623	26.692	42.590	578	0.001
Workshop	30.914	45.541	623	23.640	40.164	578	0.004
Counseling	4.222	9.348	623	3.051	6.945	578	0.015

improvement was driven mainly by loss prevention—receiving training lowers the likelihood of incurring financial loss, but has little impact on the likelihood of achieving "good" performance (defined below).

The performance is measured by earnings. For entrepreneurs in general, earnings are an important source of household income and of subsequent business growth.[20] Specifically, I examine three types of earnings: operating profit, business profit and entrepreneurial income. The business profit is defined as the difference between average monthly revenue and expenses for the most recent business. The operating profit is the business profit plus business loan interest payments (if applicable).[21] [22] And the entrepreneurial income is the business profit plus monthly salary and minus personal loan interest payment. Compared with the other two earnings measures, the entrepreneurial income is the direct measure of return to entrepreneurship, as it represents the amount of net earnings from participating in entrepreneurship. To account for the highly skewed nature of

[20] Even for those pursuing entrepreneurship mainly for subjective utility (e.g. autonomy), earnings are an important indicator of performance as it determines whether the businesses can stay afloat.

[21] The loan interest payment is computed as a product of loan amount and interest rate.

[22] Strictly speaking, the operating profit should also include tax payment. Unfortunately the GATE dataset does not contain that information. Whereas the measure being used in the anlaysis is approximate to the actual one (with tax included) in terms of the *amount*, the *signs* of the two are exactly the same. To see this, sign(actual operating profit) = sign(earnings before tax (EBT) + business loan interest payment) = sign(net profit + tax payment + business loan interest payment) = sign(net profit + business loan interest payment). The last equation holds because: if EBT ≤ 0, then tax payment is 0; if EBT > 0, then net profit is positive because it is a portion of EBT, and both sign(operating profit) and sign(net profit + business loan interest payment) are always positive. This result establishes the accuracy of the statistical evidence on the likelihood of incurring operating loss (profit).

each earnings measure, I use the natural-log form $sign(earnings) \cdot log(|earnings|+1)$.

Table 2.3 summarizes the earnings measures. The majority (about 60 percent) of the entrepreneurs had positive earnings, and 15-20 percent incurred financial loss. The treatment group performed better than the control group at both the extensive and intensive margins. The patterns are consistent for all the three measures. The treatment group also paid themselves slightly more in salary (though the difference is not statistically significant), and took out more non-salary transfer payment.

Figure 2.1 demonstrates the kernal density distribution of the earnings measures. It seems that receiving training improves earnings not by shifting the entire distribution to the right, but by substituting for some possibility of low earnings with the possibility of higher earnings. Hence the thickness of the left tail, which represents the likelihood of incurring financial loss, is trimmed. On the other hand, training imparts a more limited impact on the right tail. In other words, the high-achieving entrepreneurs did not seem to benefit much from taking training.

Table 2.4 presents the regression results that confirm the patterns above. In Panel (a), the OLS estimates suggest an improvement in the mean of the earnings. Panels (b) and (c) demonstrate the effects on the tails of the earnings distribution. Following the empirical literature that study the second moments of distributions (e.g. Chava et al. (2013)), I define the threshold for the left (right) tail as the 25-percent (75-percent) quantile of the sample. In this sample, the threshold for the left tail coincides with 0 for all three earnings measures. In the regressions, the dependent variables are binary indicators of the earnings being smaller (larger) than the threshold for the left (right) tail. The estimates from both the logistic and the two-stage instrumental variable regressions suggest that taking training effectively reduced the likelihood of having earnings in the left tail, but had little impact on achieving performance in the right tail. According to the LATE estimates, an additional hour of training decreases the likelihood of financial loss by 0.6-0.8 percentage points.[23] Using linear projection, this translates into an effect of 6-8 percentage points for receiving 10 hours

[23] In addition, I use simultaneous quantile regressions to estimate the effects of taking training on the 5, 10, 25, 75, 90 and 95 percent quantiles of the earnings distribution. The results are consistent with those from the other regressions, and are available upon request.

Table 2.3: Financial Performance: Treatment vs. Control Group

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Binary Indicators:							
Had Positive Operating Profit	0.648	0.477	520	0.594	0.492	475	0.077
Had Positive Business Profit	0.633	0.483	520	0.568	0.496	475	0.039
Had Positive Entrepreneurial Income	0.685	0.465	520	0.619	0.486	475	0.030
Had Negative Operating Profit	0.144	0.352	520	0.200	0.400	475	0.020
Had Negative Business Profit	0.150	0.357	520	0.204	0.404	475	0.025
Had Negative Entrepreneurial Income	0.162	0.368	520	0.240	0.428	475	0.002
Amount (Log $):							
Monthly Business Revenue	6.914	2.662	544	6.741	2.866	502	0.314
Monthly Business Expenses	6.588	2.451	548	6.665	2.369	495	0.609
Monthly Operating Profit	3.492	4.983	520	2.854	5.321	475	0.052
Monthly Business Profit	3.370	5.033	520	2.681	5.341	475	0.037
Monthly Entrepreneurial Income	3.828	5.085	520	2.983	5.644	475	0.013
Monthly Salary for Self and Family	1.821	3.228	590	1.599	3.126	555	0.239
Total Non-Salary Transfer	1.589	3.378	615	1.203	2.961	576	0.037

Notes:
[i] Net profit equals business revenue minus expenses.
[ii] Operating profit equals net profit plus business loan interest payments (if any).
[iii] Entrepreneurial income equals net profit plus salary and minus personal loan interest payment.

of training. This effect is not trivial, considering that the sample's likelihood of incurring financial loss is 15-20 percentage points.

2.5 Analysis 2: Business Financing

In Analysis 2, I show that receiving training reduces the entrepreneurs' capital investment in production. I proxy capital investment by its antecedent—business financing. Financing is a valid proxy because small businesses typically raise money to exclusively finance their production activities. The analysis shows that taking training decreases the start-up financial capital. This is consistent with the prediction by the prudence mechanism where entrepreneurs learned to reduce

Figure 2.1: Treatment Group Had Better Financial Performance

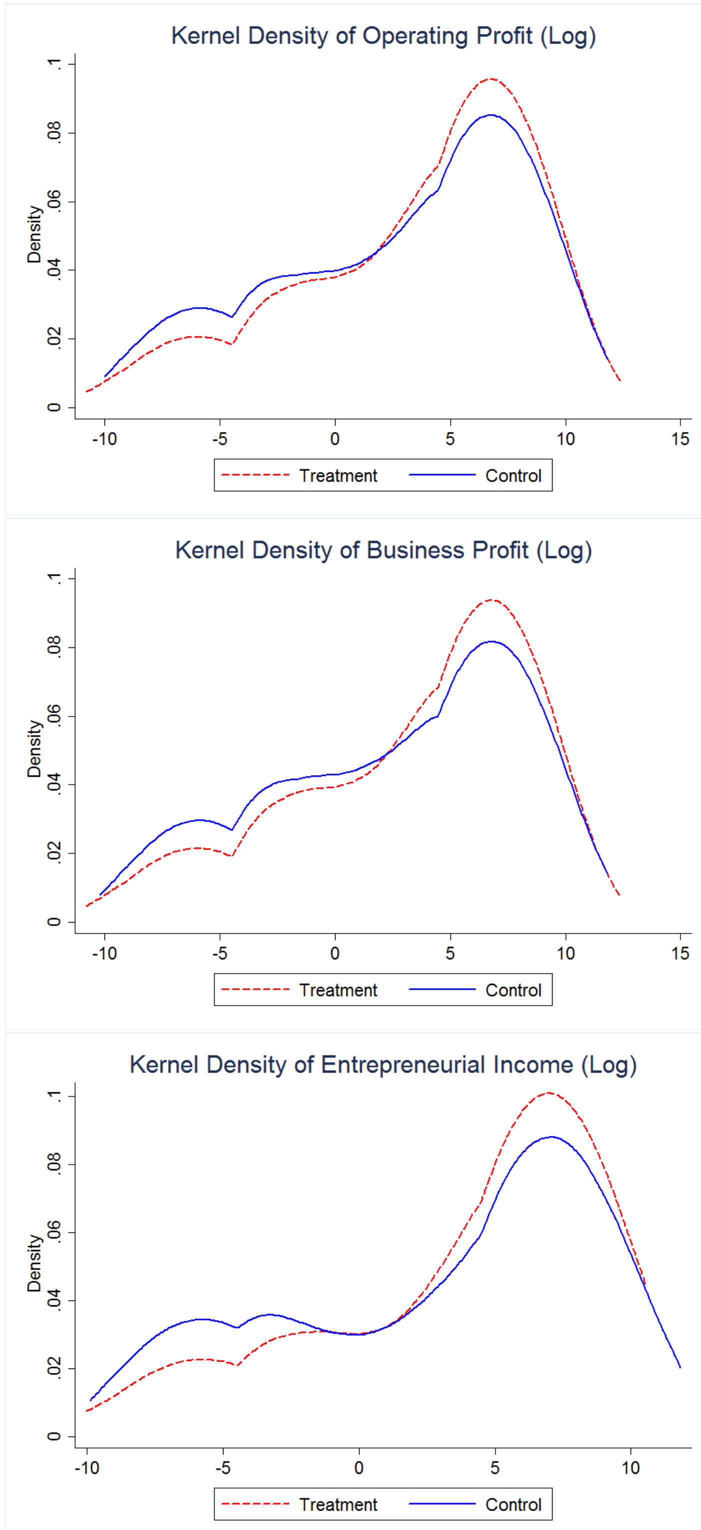


Table 2.4: The Improvement on Earnings Concentrates on Loss Prevention

(a) OLS Regressions

	Operating Profit	Business Profit	Entrepreneurial Income
	(1)	(2)	(3)
Treatment	0.617*	0.657*	0.728**
	(0.341)	(0.344)	(0.352)
Log Likelihood	-2836.940	-2845.234	-2869.701
N	935	935	935

(b) Logistic Regressions

	Operating Profit		Business Profit		Entrepreneurial Income	
	< 25% Sample	> 75% Sample	< 25% Sample	> 75% Sample	< 25% Sample	> 75% Sample
	(Quantile = 0)	(Quantile = 1415)	(Quantile = 0)	(Quantile = 1300)	(Quantile = 0)	(Quantile = 2000)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.472***	0.090	-0.439**	0.064	-0.565***	-0.124
	(0.181)	(0.160)	(0.179)	(0.160)	(0.173)	(0.160)
Log Likelihood	-403.088	-491.749	-411.421	-494.597	-434.464	-491.287
N	935	932	935	932	935	935

(c) Two Stage Instrumental Variables Regressions

	Operating Profit		Business Profit		Entrepreneurial Income	
	< 25% Sample	> 75% Sample	< 25% Sample	> 75% Sample	< 25% Sample	> 75% Sample
	(Quantile = 0)	(Quantile = 1415)	(Quantile = 0)	(Quantile = 1300)	(Quantile = 0)	(Quantile = 2000)
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage:						
Hours of Training	-0.017**	0.002	-0.006*	0.001	-0.008**	-0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
First Stage:						
Treatment	9.920***	9.920***	9.920***	9.920***	9.920***	9.920***
	(2.933)	(2.980)	(2.980)	(2.980)	(2.980)	(2.980)
F-stat (Treatment = 0)	11.084	11.084	11.084	11.084	11.084	11.084
R-squared	0.065	0.065	0.065	0.065	0.065	0.065
N	935	935	935	935	935	935

Notes:
[i] Heteroskedasticity-consistent standard errors are in parentheses.
[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.

value-destroying investment.

For a general illustration, Figure 2.2(a) presents the kernal density of the total start-up capital. The two groups shared a very similar left tail of the distribution, but the treatment group had a substaintially thinner right tail. Whereas entrepreneurs with all levels of financing may be affected by the training, it was those with a larger amount that seemed more sensitive.

Specifically in the analysis, I divide the total financial capital into debt financing and the entrepreneurs' own-money input. The statistical evidence suggests: the entrepreneurs with more training were less likely to borrow money for business; their own-money commitment and total start-up capital were also more moderate, and the impacts of training were more pronounced on the larger amounts. Those with smaller amount of start-up capital were more likely to be liquidity-constrained, and thus less likely to make excessive investment.

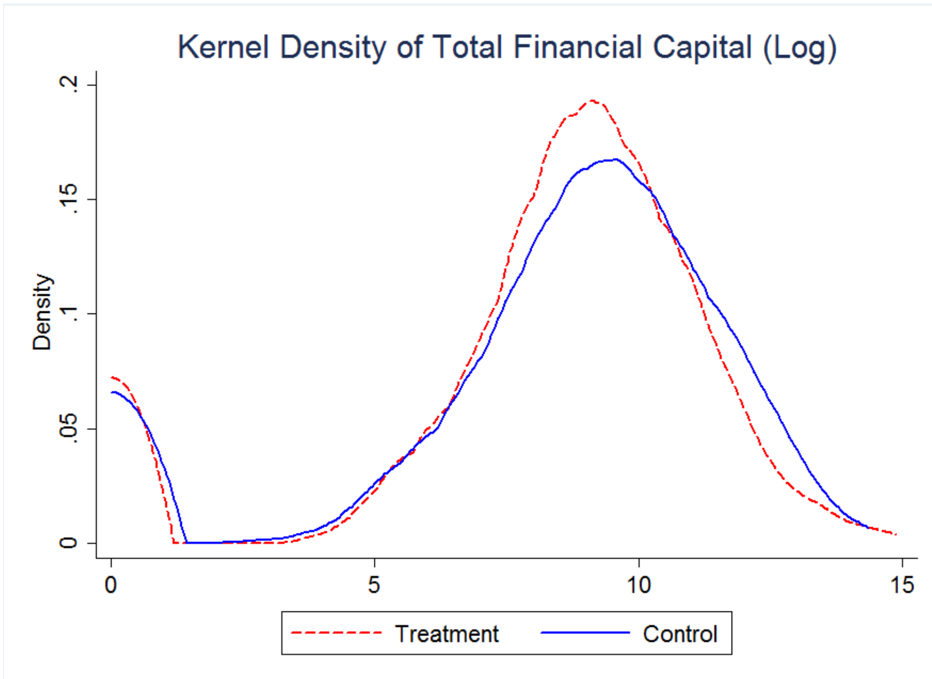
I start by examining the entrepreneurs' use of debt. Debt financing is a strong indicator of more aggressive capital investment, because entrepreneurs generally would pursue external sources only after they exhaust their own savings and external equity financing is very scarce for nascent businesses (Myers and Majluf, 1984; Berger and Udell, 1998).

Table 2.5 shows that about a quarter of the entrepreneurs borrowed money over the history of their most recent businesses, and that the treatment group was less likely to do so than the control group. This difference mainly manifests itself in personal loans (loans taken out in the name of the entrepreneurs). In contrast, a smaller percentage of the entrepreneurs used business loans (loans issued to businesses) and the percentages are virtually the same between the two groups. The lower popularity of business loans among the entrepreneurs, as well as its insensibility to training, may possibly be attributed to the stricter criteria for approval. The typical criteria on cash flow, collateral (e.g. patents) and financial performance pose a particularly harsh barrier for nascent entrepreneurs.[24] Those applying to business loans tended to satisfy such criteria, and were better entrepreneurs than the general, thus their financing decisions were less likely to be affected

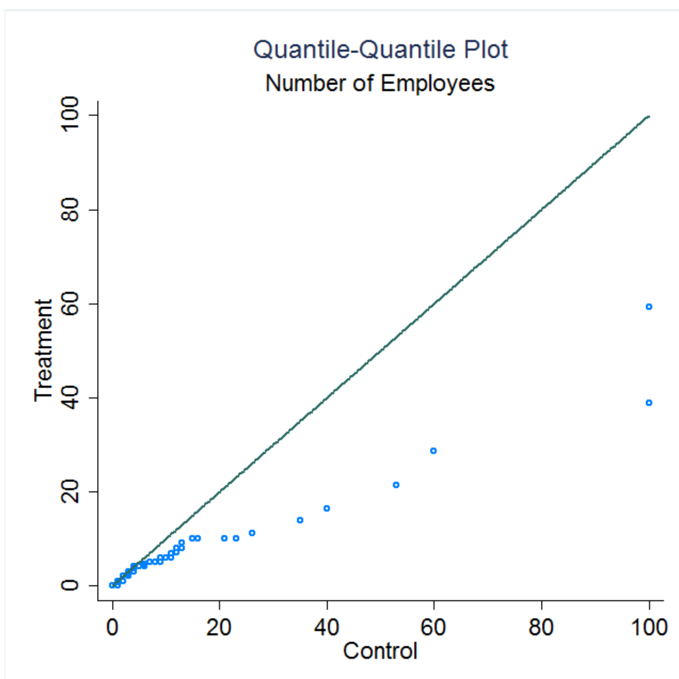
[24] A professional business trainer with extensive experience in small business financing, Glamis Haro (introudced in Section 2.7), confirmed that it is difficult for nascent businesses to obtain business loans. She said, "Most banks consider only businesses that are at least three years old and profitable."

Figure 2.2: Receiving Training Leads to Smaller Financing and Production Scale

(a)



(b)



by either the productivity or prudence mechanism.[25] On the other hand, personal loans, such as those provided by the individuals' credit cards, families or friends, are more accessible and seldom require close scrutiny over the entrepreneurs' businesses before approval.

Both the logistic and two-stage instrumental variable regressions confirm the effects of receiving training on loan use. The LATE coefficient suggests that receiving an additional hour of training decreases the likelihood of debt financing by 0.7 percent.

Conditional on borrowing, the cost of debt financing (interest rate) does not seem to vary with the amount of the entrepreneurs' training. Table 2.6 profiles the the personal loans in the upper panel and the business loans in the lower one. The characteristics being examined include loan amount, duration, interest rate and sources.

For both personal and business loans, the two groups differ very little in duration and interest rate. And the average annual interest rates are around 8 percent. This suggests that the reduced borrowing by the treatment group was unlikely to be driven by aversion from usurious loans, for if that were the case, the treatment group should on average have paid a lower interest rate than the control group, and the control group's average interest rate should have been significantly higher than its current level. The annual interest rates for the usurious loans are typically higher than 8 percent by orders of magnitude. For example, the payday loans charge over 400 percent for annual interest rate (Bertrand and Morse, 2011).

In addition, the treatment group seemed to borrow less in loan amount than the control group. The difference is non-trivial in magnitude, but is not statistically significant (possibly due to low statistical power from the small number of loans.). The difference in the average amount is about 8,000 USD for personal loans and 20,000 USD for business loans.

Echoing findings by Robb and Robinson (2012), services provided by traditional financial institutions, such as credit cards, personal mortgage and bank loans, represent the major sources of credit. To a lesser extent, entrepreneurs also borrowed from family, friends, government agencies

[25]The average operating profit (log) of the entrepreneurs with business loans is 4.392, higher than the sample average (3.188). The difference is statistically significant (t-statistic = 2.168). It is also higher than the average of the entrepreneurs that borrowed personal loans for business (2.859). The difference is also statistically significant (t-statistic = 2.206).

and investment companies. Both groups shared similar distributions of financing sources, except that the treatment group was more likely to use SBA-backed loans in lieu of regular bank loans.[26] This finding seems reasonable (and natural), as SBA is a major provider of the GATE training services.

Next, I examine the entrepreneurs' own-money commitment and the total financial capital for their most recent businesses. For each entrepreneur, the total amount of financial capital in her business is computed as $(I+G+O+D)/p+B$, where I denotes the amount of the entrepreneurs' own-money input, G the amount of money from grants, O the amount of non-debt capital from other sources (e.g. gifts), D the amount borrowed from personal loan, B the amount from business loan and p the share of her equity in the business.

In Table 2.7, I show that the treatment group committed less of their own money and also raised less total capital for the business.[27] In Panel (a), receiving training decreases the average amount of financing. Panels (b) and (c) confirm that the effects of training are more pronounced for the right tail of the distribution. The estimates from logistic regressions in Panel (b) suggest that the treatment group was significantly less likely to commit a large amount of their own money or raise a large amount of total capital, "large" being defined as exceeding the 75-percent quantile of the sample. But the effects on the left tail (below 25-percent of the sample) appear small, implying the smaller amounts of financing may be less sensitive to receiving training. In Panel (c), the two-stage instrumental variable regressions estimate the marginal effects: receiving 10 additional hours of training reduces the likelihood of large-amount financing by 5 percentage points.[28]

[26]The SBA offers an array of loan-guarantee programs aimed at helping small businesses to grow and survive diasters. For a list of their programs, see http://www.sba.gov/loanprograms (accessed Oct 10, 2014).

[27]To account for the skewed nature of the amounts, I use theri natural-log form: $log(original+1)$.

[28]About 10 percent of both the treatment and the control groups had zero total financial capital and own-money input (hence the "hump" at the left tail in Figure 2.2(a)). Their revenue distribution is similar to that of the others. As only fewer than 10 entrepreneurs received their business as heritage or gift, the null capital raises concern about mis-reporting (perhaps due to memory decay, as start-up capital was mostly committed at the birth of the businesses). The mis-reporting is likely to bias the estimated effect towards 0 as the actual financing is likely to be larger for the control group. Therefore, the regressions in Table 2.7 exclude those null-capital businesses.

Table 2.5: Receiving Training Reduces Debt Financing

(a) Descriptive Statistics

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Binary Indicators:							
Used Any Loan for Business	0.226	0.419	619	0.283	0.451	576	0.024
Used Personal Loan for Business	0.143	0.350	616	0.209	0.407	573	0.003
Used Business Loan	0.117	0.322	616	0.119	0.324	573	0.924

(b) Intent-to-Treat Models

	Used Any Loan (Logistic)	Used Personal Loan (Logistic)	Used Business Loan (Logistic)	Loan Amount ($1000) (Tobit)
	(1)	(2)	(3)	(4)
Treatment	-0.376***	-0.543***	-0.100	-45.666**
	(0.144)	(0.167)	(0.195)	(18.499)
Log Likelihood	-606.343	-490.915	-382.104	-2075.133
N	1112	1106	1105	1091

(c) LATE Models

	Used Any Loan (2SLS)	Used Personal Loan (2SLS)	Used Business Loan (2SLS)	Loan Amount ($1000) (IV Tobit)
	(1)	(2)	(3)	(4)
Second Stage:				
Hours of Training	-0.007**	-0.008**	-0.001	-4.634**
	(0.004)	(0.003)	(0.002)	(2.292)
First Stage:				
Treatment	9.294***	9.301***	9.301***	9.869***
	(2.694)	(2.700)	(2.700)	(2.709)
F-stat (Treatment = 0)	11.905	11.868	11.868	
R-squared	0.054	0.054	0.054	
N	1116	1110	1110	1091

Notes:
[i] Heteroskedasticity-consistent standard errors are in parentheses.
[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.

Table 2.6: Loan Characteristics Conditional on Borrowing

(a) Personal Loans

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Loan Amount ($1000)	62.349	152.790	77	70.622	169.037	104	0.735
Loan Duration (years)	9.229	9.508	59	10.558	10.550	77	0.449
Annual Interest Rate (%)	8.532	6.089	62	8.253	6.463	87	0.790
Sources:							
Credit Cards (%)	28.409	45.356	88	27.500	44.839	120	0.886
Personal Mortgages (%)	42.045	49.646	88	36.667	48.391	120	0.434
Family (%)	19.318	39.706	88	21.667	41.370	120	0.681
Friends (%)	10.227	30.474	88	12.500	33.211	120	0.614
Others (%)	13.636	34.514	88	20.000	40.167	120	0.233

(b) Business Loans

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Loan Amount ($1000)	82.340	151.480	63	101.612	186.307	60	0.529
Loan Duration (years)	7.232	5.337	50	9.091	9.008	52	0.210
Annual Interest Rate (%)	7.727	3.385	44	7.220	2.636	50	0.417
Sources:							
Regular Bank Loans (%)	62.500	48.752	72	80.882	39.615	68	0.016
SBA-Backed Loans (%)	15.278	36.230	72	5.882	23.704	68	0.073
Other Gov't Agency Loans (%)	4.167	20.123	72	1.471	12.127	68	0.342
Investment Companies (%)	1.389	11.785	72	0.000	0.000	68	0.333
Others (%)	15.278	36.230	72	11.765	32.459	68	0.548

Table 2.7: Receiving Training Decreases Own-Money Financing and Total Capital in Business

(a) OLS Regressions

	Own-Money Input	Total Financial Capital
	(1)	(2)
Treatment	-0.394**	-0.300**
	(0.171)	(0.126)
R-squared	0.088	0.161
N	862	862

(b) Logistic Regressions

	Own-Money Input		Total Financial Capital	
	< 25% Sample	> 75% Sample	< 25% Sample	> 75% Sample
	(Quantile = 2000)	(Quantile = 20000)	(Quantile = 3000)	(Quantile = 40000)
	(1)	(2)	(3)	(4)
Treatment	0.249	-0.377**	0.183	-0.498***
	(0.173)	(0.175)	(0.173)	(0.176)
Log Likelihood	-432.105	-415.219	-423.957	-419.179
N	858	862	858	862

(c) Two-Stage Least Squares Instrumental Variable Regressions

	Own-Money Input		Total Financial Capital	
	< 25% Sample	> 75% Sample	< 25% Sample	> 75% Sample
	(Quantile = 2000)	(Quantile = 20000)	(Quantile = 3000)	(Quantile = 40000)
	(1)	(2)	(3)	(4)
Second Stage:				
Hours of Training	0.003	-0.005*	0.003	-0.006**
	(0.002)	(0.003)	(0.002)	(0.003)
First Stage:				
Treatment	12.212***	12.212***	12.212***	12.212***
	(3.095)	(3.095)	(3.095)	(3.095)
F-stat (Treatment = 0)	15.570	15.570	15.570	15.570
R-squared	0.075	0.075	0.075	0.075
N	862	862	862	862

Notes:

[i] The regressions exclude businesses with 0 total capital due to concern for mis-reporting.

[ii] Heteroskedasticity-consistent standard errors are in parentheses.

[iii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[iv] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.

2.6 Analysis 3: Production Scale and Its Growth

In Analysis 3, I proxy the capital investment in production with its consequence—the production scale and its growth, and show that receiving training decreases both. The production scale increases with the amount of capital investment. In the analysis, the scale is measured by the number of employees in the business (excluding the entrepreneurs themselves). And the growth is defined by the increase in their employment size since the previous survey. This increase reflects the size of the incremental capital invested in production, as well as the amount of new employment created. The results from this analysis support the prudence mechanism.

Figure 2.2(b) compares the distribution of the employment size between the treatment and the control groups. The quantile-quantile plot suggests that the treatment group had fewer employees, and the difference is driven mainly by the control group having a fatter right tail.[29] This is consistent with the aforementioned findings on the financing scale, and further supports the prudence mechanism where entrepreneurs learned to reduce their overconfident investments.

The statistical evidence is presented in Table 2.8. In Panel (a), the entrepreneurs in the treatment group are shown to have had a lower average employment size than those in the control group. Receiving training also leads to a more moderate increase in employment size. Moverover, the differential changes in the employment size seems to be driven primarily by the growth of continuing businesses than the new entrepreneurial entries. A minority (about 25 percent) of the entrepreneurs in both groups were new, i.e., reporting no entrepreneurial experience in the 2nd survey. Those continuing businesses in both groups had similar and small employment sizes in the second survey. This is likely due to their very young age back then (median age equal to 18 months at the second survey date). At that stage, most entrepreneurs either did not have a plan for

[29]To see this, if two distributions were identical, then all the dots would reside on the 45-degree line. In this plot, however, the dots on the left are on or closely below that line, and the dots on the right are below that line by a wider margin. This implies that for a given small percentage (e.g. 10 percent), the corresponding quantile in the treatment group's distribution is similar to the same quantile in the control group's; for a given large percentage (e.g. 90 percent), the corresponding quantile in the treatment group's distribution is significantly smaller than the same quantile in the control group's. The same pattern appears in a cumulative density graph (available upon request). The quantile-quantile plot is displayed here because a large portion of the entrepreneurs did not have employees, making the comparison less clear visually in a density graph.

expansion, or had not raised sufficient money even if they already developed an expansion plan.

Panels (b) and (c) present the regression results. The results confirm the negative effects of receiving training on the production scale and its growth. To account for the discrete, non-negative and over-dispersed nature of the employment size, poisson and negative binomial models are fitted.[30] The two-stage instrumental variable models suggest that receiving an additional 10 hours of training decreases the production scale and slows its growth by about one employee.

2.7 Analysis 4: Opinion-Based Evidence

In Analysis 4, I present some direct evidence on the primary mechanism—the opinions of the trainees and the trainers. The opinions support the prudence mechanism—the individuals reported "refining business ideas" as a major way that training helped them, and the trainers reported "unrealistic expectations", "lack of focus" and "underestimating costs" as common issues that challenged entrepreneurs.

To elaborate, the evidence is two-fold. First, in the GATE sample, the individuals that received training were asked to rate how much training helped with each of 13 issues. For each issue, the question in the survey is "I am going to read a list of ways self-employment services you received in the past 12 months may have helped you. Please tell me whether self-employment services helped you a lot, somewhat, or not at all in [issue]." As shown in Table 2.9, I classify the 13 issues into 3 categories. Category 1 relates to business planning and includes 3 issues "developing a business plan", "deciding whether to pursue self-employment" and "refining business idea". Category 2 relates to specific functions in business operation and includes 8 issues: "applying for loans", "dealing with credit issues", "developing marketing strategy", "dealing with legal issues" and "dealing with accounting issues" etc. Category 3 includes the remaining 2 issues that do not fall under the previous 2 categories: "networking" and "providing psychological support". For each issue, the individuals' response is recorded on a Likert scale with 3 values: "a lot", "somewhat"

[30] In addition, I also run an OLS regression and obtain qualitatively similar results. The coefficient estimate for the treatment dummy is -0.906 with standard deviation of 0.355.

Table 2.8: Receiving Training Decreases Production Scale and Its Growth

(a) Descriptive Statistics

	Treatment			Control			F-test
	mean	st. dev	N	mean	st. dev	N	p-value
Number of Employees	1.016	3.760	617	1.748	7.566	575	0.033
Change in Employment							
of all entrepreneurs	0.246	2.894	609	1.028	6.803	564	0.010
of continuing entrepreneurs	0.102	2.897	469	0.663	5.276	412	0.048
of new entrepreneurs	0.729	2.843	140	2.020	9.769	152	0.133

(b) Intent-to-Treat Effects

	Number of Employees		Employment Change
	(Poisson)	(Negative Binomial)	(OLS)
	(1)	(2)	(3)
Treatment	-0.676***	-0.516***	-0.779**
	(0.207)	(0.161)	(0.318)
Log Likelihood	-2941.663	-1307.684	
R-squared			0.052
N	1114	1114	1097

(c) Two-Stage Least Squares Instrumental Variable

	Number of Employees	Employment Change
	(1)	(2)
Second Stage:		
Hours of Training	-0.095**	-0.079**
	(0.046)	(0.040)
First Stage:		
Treatment	9.568***	9.851***
	(2.715)	(2.735)
F-stat (Treatment = 0)	12.423	12.970
R-squared	0.057	0.059
N	1114	1097

Notes:
[i] Heteroskedasticity-consistent standard errors are in parentheses.
[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.

and "not at all". Table 2.9 presents the distribution over these 3 values.

The individuals were substantially more (less) likely to report training helping them "a lot" ("not at all") with the business planning issues than with the functions in business operation. This echoes the finding that the entrepreneurs with more training were more likely to have written business plans. In particular, 37 percent of the individuals reported training helping "a lot" with "refining business idea", compared with around 20 percent or less for the skills for business operation; and 25 percent of the individuals reported training helping "not at all" with "refining business idea", compared with 34-75 percent for the skills for business operation.[31]

In addition, training was most helpful with "refining business idea" and "networking". Combining this with the findings from previous analyses, the refining and networking seemed to have revised down the entrepreneurs' investment. This is consistent with the prudence mechanism where knowledge gained from the trainers or peers mitigates overconfidence.

Second, I also interviewed two business trainers at a small business development center in New York City. The center is one of the many operated by the SBA that offer training services similar to those in GATE. Part of the GATE training was conducted in local small business development centers.

The two trainers were intervewed separately. The first trainer, Lawrence King, has over twenty years' experience in advising entrepreneurs. When asked what were the common issues addressed by the counseling sessions, he talked about two issues. The first is that nascent entrepreneurs tend to hold unrealistic expectations:

> "Many people are aggressive with their financial analysis. Even at the start, some expect to launch their businesses on a national basis and make a million dollars. I often have to be blunt with them, manage their expectations and tell them to cut back on the fancy chairs and refrigerators."

The second issue is that nascent entrepreneurs often lack focus:

[31] These differences are statistically significant. Results of the F-tests are available upon request.

Table 2.9: How Much did Training Help with the Following Issues?

	Percentage for Each			
	"A lot."	"Somewhat."	"Not at all."	N
Business Planning:				
Developing business plan	27.79	38.30	33.91	637
Deciding whether to pursue self-employment	31.23	31.72	37.06	618
Refining business idea	37.42	37.73	24.85	652
Specific Functions in Business Operation:				
Applying for loans	7.52	17.66	74.83	572
Dealing with credit issues	12.40	25.94	61.66	613
Developing marketing strategy	27.58	43.91	28.51	649
Dealing with legal issues	14.06	33.39	52.56	626
Dealing with accounting issues	15.70	32.81	51.49	637
Hiring and dealing with employees	10.98	27.70	61.32	592
Using computer and other technology	24.41	28.95	46.64	639
Dealing with clients	26.36	39.53	34.11	645
Other Issues:				
Networking	38.28	39.36	22.36	653
Providing psychological support	18.11	31.34	50.55	635

Notes:
Responses were provided by individuals that had received business training over the past 12 months.

> "Seventy-five percent of people have no clue, no plan and no consideration of cost. In one case, the person wanted to blend floral shop, ice-cream and locksmith into one business . . . Many just have not thought about the details, need to put a dollar sign on their thinking. I'm here to help them get a long-term view."

The second trainer, Glamis Haro, specializes in business plan development, credit management and microenterprise financing. She commented on the entrepreneurs' underestimation of costs:

> "They're often confused about the obligations as employers, such as employment tax obligations, medical insurance and others according to the regulations. A lot of business owners don't know they have to provide those things for their employees."

In addition, she provided more details on how training helps with entrepreneurs' forecasting:

> "They don't know the importance of a cash flow statement evaluation and what it means for their business. Money comes in, money goes . . . We ask them to bring their cash flow numbers, then we'll run the projection using our model. We also check the industry statistics. Sometimes they get eager when forecasting their revenue, and over project their profits."

2.8 Robustness Checks

In this section, I conduct three sets of robustness checks on the empirical results presented above. First, I check that the results are not driven by the heterogeneous attrition rates between the treatment and the control groups. Second, I show that the results are robust to alternative sampling strategies. And third, additional statistical analyses suggest that the empirical findings are unlikely driven by improved production efficiency.

2.8.1 Heterogeneous Attrition

The treatment group was more likely to complete the survey than the control group, as evidenced by the number of observations in each group. This raises the concern that the differential attrition rates may be potentially driven by unobserved characterisitics, such as interest in entrepreneurship, that would also affect the indivduals' behavior and performance. This issue may potentially affect the consistency of the regression estimators. To address this, I use weighted regressions, where the sample weights are constructed in a way that compensates for the absence of the attriters (Fairlie et al., 2012). A logistic model with only the control variables (specified in Section 2.3.1) on the right hand side is estimated to predict the likelihood of response. The predicted probability is then inversed to be used as sample weights. Then the regressions in Analyses 1-3 are re-run with the sample weights. As Table 2.10 summarizes, the estimates remain very similar to the original ones. This suggests that heterogeneous attrition is unlikely a driver of the empirical findings.

2.8.2 Alternative Sampling Strategy

I run the regressions in Analyses 1-3 using the two alternative samples as defined in Section 2.3.1. As summarized in Tables 2.11 and 2.12, the results remain similar to the ones using the default sample. The results based on the full sample suggest that by taking training, the average individual with a business idea can expect to decrease investment but improve entrepreneurial performance. And her chances of entering business ownership would not be changed by training (Table 2.1). In addition, the estimates using the Heckman selection model suggest that the effects hold if all the individuals in the full sample had been business owners.

Analyses based on the three samples consistently suggest the causal effect: receiving training produces smaller but better performing businesses. The results also suggest that this causal effect is due to mitigating overconfidence conditional on business ownership, rather than training selecting the less overconfident individuals into entrepreneurship. The rationale is three-fold. First, both groups had almost identical rate of business ownership. If receiving training screens out the very overconfident, then we should observe a lower entry rate for the treatment group (Lerner and

Table 2.10: Weighted Regressions to Address Heteogeneous Attrition

(a) Likelihood of Loss (Logistic Regressions)

	Operating Profit was Negative	Business Profit was Negative	Entrepreneurial Income was Negative
	(a1)	(a2)	(a3)
Treatment	-0.372**	-0.345*	-0.495**
	(0.189)	(0.186)	(0.179)
Log Likelihood	-401.485	-408.811	-429.195
N	935	935	935

(b) Financing (Logistic Regressions)

	Used Any Loan	Own-Money Input Above 75% of Sample	Total Financial Capital Above 75% of Sample
	(b1)	(b2)	(b3)
Treatment	-0.319**	-0.377**	-0.390**
	(0.150)	(0.175)	(0.167)
Log Likelihood	-598.021	-415.219	-448.636
N	1112	862	862

(c) Production Scale and Growth

	Number of Employees		Change in Number of Employees
	(Poisson)	(Neg Binomial)	(OLS)
	(c1)	(c2)	(c3)
Treatment	-0.717***	-0.453***	-0.888**
	(0.217)	(0.158)	(0.410)
R-Squared			0.038
Log Likelihood	-4919.200	-2205.030	
N	1114	1114	1097

Notes:
[i] Heteroskedasticity-consistent standard errors are in parentheses.
[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.
[iv] All regressions are weighted. The weights are inverse predicted probability of continuing to be surveyed. See Section 2.8.1 for details.
[v] Regressions (b2) and (b3) exclude businesses with 0 total capital due to concern for mis-reporting.

Table 2.11: Regressions Using Sample of Business Owners since Random Assignment

(a) Likelihood of Loss (Logistic Regressions)

	Operating Profit was Negative	Business Profit was Negative	Entrepreneurial Income was Negative
	(a1)	(a2)	(a3)
Treatment	-0.363**	-0.343**	-0.441***
	(0.153)	(0.152)	(0.148)
Log Likelihood	-547.681	-554.938	-576.733
N	1168	1168	1168

(b) Financing (Logistic Regressions)

	Used Any Loan	Own-Money Input Above 75% of Sample	Total Financial Capital Above 75% of Sample
	(b1)	(b2)	(b3)
Treatment	-0.300**	-0.462***	-0.364**
	(0.131)	(0.155)	(0.158)
Log Likelihood	-738.872	-525.864	-511.886
N	1428	1033	1033

(c) Production Scale and Growth

	Number of Employees		Change in Number of Employees
	(Poisson)	(Neg Binomial)	(OLS)
	(c1)	(c2)	(c3)
Treatment	-0.442*	-0.394**	-0.698**
	(0.237)	(0.163)	(0.275)
R-Squared			0.022
Log Likelihood	-3555.487	-1495.472	
N	1367	1367	1269

Notes:
[i] Heteroskedasticity-consistent standard errors are in parentheses.
[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.
[iv] Regressions (b2) and (b3) exclude businesses with 0 total capital due to concern for mis-reporting.

Table 2.12: Regressions Using Full Sample Regardless of Entrepreneurial Experience

(a) Likelihood of Loss (Logistic Regressions)

	Operating Profit was Negative	Business Profit was Negative	Entrepreneurial Income was Negative
	(a1)	(a2)	(a3)
Treatment	-0.342**	-0.323**	-0.412***
	(0.145)	(0.144)	(0.140)
Log Likelihood	-680.022	-690.044	-724.177
N	2046	2046	2046

(b) Financing (Logistic Regressions)

	Used Any Loan	Own-Money Input Above 75% of Sample	Total Financial Capital Above 75% of Sample
	(b1)	(b2)	(b3)
Treatment	-0.251**	-0.198*	-0.247**
	(0.125)	(0.117)	(0.119)
Log Likelihood	-875.143	-916.053	-895.741
N	2213	1823	1823

(c) Production Scale and Growth

	Number of Employees		Change in Number of Employees
	(Poisson)	(Neg Binomial)	(OLS)
	(c1)	(c2)	(c3)
Treatment	-0.488*	-0.312*	-0.544***
	(0.252)	(0.165)	(0.201)
R-Squared			0.005
Log Likelihood	-4282.727	-1674.684	
N	2225	2225	2162

Notes:
[i] Heteroskedasticity-consistent standard errors are in parentheses.
[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.
[iv] Regressions (b2) and (b3) exclude owners of businesses with 0 total capital due to concern for mis-reporting.

Table 2.13: Heckman Selection Models Using Full Sample

(a) Likelihood of Loss

	Operating Profit was Negative	Business Profit was Negative	Entrepreneurial Income was Negative
	(a1)	(a2)	(a3)
Treatment	-0.063***	-0.060**	-0.083***
	(0.024)	(0.025)	(0.026)
Mills Ratio	-0.292	-0.350*	-0.379*
	(0.185)	(0.193)	(0.202)
N	1725	1725	1725

(b) Financing

	Used Any Loan	Own-Money Input Above 75% of Sample	Total Financial Capital Above 75% of Sample
	(b1)	(b2)	(b3)
Treatment	-0.069***	-0.056**	-0.079***
	(0.026)	(0.028)	(0.028)
Mills Ratio	-0.164	-0.180	-0.011
	(0.186)	(0.227)	(0.223)
N	1906	1652	1652

(c) Production Scale and Growth

	Number of Employees	Change in Number of Employees
	(c1)	(c2)
Treatment	-0.903***	-0.779**
	(0.346)	(0.316)
Mills Ratio	-2.374	0.309
	(2.497)	(2.209)
N	1904	1887

Notes:

[i] Heteroskedasticity-consistent standard errors are in parentheses.

[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.

[iv] Regressions (b2) and (b3) exclude owners of businesses with 0 total capital due to concern for mis-reporting.

Malmendier, 2013). Second, business owners in both groups were observationally very similar. As overconfidence is related to demographics (Barber and Odean, 2001), the selection would have resulted in inter-group difference. Third, if the effect had been driven by selection, then the two groups should differ at both tails of the distributions in Figure 2.2. However, we only observe difference at the right tail. This is consistent with the prudence mechanism: compared with samller investments, the larger ones are more likely to be driven by overconfidence, and thus are more likely to be reduced by training.

2.8.3 Alternative Explanation: Productivity

A possible alternative explanation for the empirical results would be that receiving training improves production efficiency, thereby motivating entrepreneurs to scale down the production factors for cost reduction. However, I show that this explanation is unlikely to drive the empirical results. The rationale is two-fold.

First, for nascent and growing businesses, improved productivity opens up the opportunity to capture greater market shares and to reap higher profit, making it unlikely for entrepreneurs to shrink their production scale. Thus the substitution between productivity and production factors does not seem intuitive, as it is inconsistent with the entrepreneurs' financial incentive. Since the vast majority of the GATE sample cannot be considered wealthy and thus are likely to rely on entrepreneurship as a source of income,[32] it seems reasonable to expect that they had incentive to gain financially. In addition, by applying to participate in the training program, they revealed their motivation to enhance their entrepreneurial performance.

Second, the statistical evidence in Table 2.14 suggests that receiving training had little impact on the production efficiency of the GATE entrepreneurs. The efficiency is measured by the ratio of average monthly revenue over the total number of workers (including the entrepreneurs).[33] In

[32] About 80 percent of the sample had annual family income of $75,000 or less. See Table 2.1.

[33] For measuring efficiency, revenue is chosen over profit for two reasons. First, productivity is commonly measured as the ratio of revenue over labor units in the literature (e.g. Griliches and Regev (1995)). Second, profit per worker is not consistent with efficiency when the profit is negative. For a given amount of negative profit, a larger number of workers would not imply higher efficiency, but profit per worker would increase with the number for workers. In

Panel (a), OLS regressions show that receiving training does not significantly affect the mean of the efficiency; And Panel (b) shows that receiving training also does not alter the likelihood of being in either the left or right tail of the efficiency distribution.

The findings confirm that the GATE sample could not significantly improve their production efficiency by taking training. But this does not suggest that entrepreneurs do not need to improve efficiency, or imply that all the practices taught in the training sessions are of limited value. Rather, it means that entrepreneurs cannot effectively learn to increase efficiency by taking training. The reason for that needs further investigation. Whereas it is possible that some skills taught by the training may not be relevant, it is also possible that the trainees could not effectively absorb or apply what was taught (Drexler et al., 2010). More fine-grained data are needed to distinguish the two.

2.9 Conclusion and Implications

Entrepreneurship can be learned, and it would be most useful for entrepreneurs to learn skills or knowledge that mitigates overconfidence and foster prudence. Using data from a randomized field experiement, I show that by participating in business training, entrepreneurs reduce their value-destorying investment. Thus, learning reduces their business financing, production scale and business growth but boosts financial performance.

This paper is among the first to focus on the mechanism whereby entrepreneurs benefit from learning. It remains to be studied whether the insights from this paper can be generalized beyond its empirical context. The context here is characterized by two dimensions. The first is the type of learning. Although the content and format of the training in GATE are common in the U.S.,[34] future work may extend our understandings by exploring other forms of learning, such

addition, the results are qualitatively similar when I measure efficiency using the total factor productivity (TFP). TFP is the residual term from regressing revenue (log) on total financial capital (log), number of workers (log) and the control variables specified in Section 2.3.1.

[34]For example, the SBA provides similar training through its 1,000 small business development centers in the U.S. See http://www.asbdc-us.org/About_Us/aboutus.html (accessed Oct 8, 2014).

Table 2.14: Receiving Training Has Little Impact on Production Efficiency

(a) OLS Regressions

	Efficiency	ln (Efficiency + 1)
	(1)	(2)
Treatment	287.673	0.165
	(630.990)	(0.162)
R-squared	0.061	0.095
N	981	981

(b) Logistic Regressions

	Efficiency	
	< 25% Sample (Quantile = 300)	> 75% Sample (Quantile = 3500)
	(1)	(2)
Treatment	-0.114	0.142
	(0.161)	(0.161)
Log Likelihood	-490.717	-494.270
N	981	981

Notes:
[i] Heteroskedasticity-consistent standard errors are in parentheses.
[ii] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[iii] All regressions control for demographics and site fixed effects. See Section 2.3.1 for details.

as other training programs, observational learning, experiential learning and so on (Tucker and Zhang, 2011; Nadler et al., 2003; Sun et al., 2012; Waguespack and Fleming, 2009). The second dimension is the type of entrepreneurs. The GATE sample consists mostly of the "main-street"-type of entrepreneurs, who own and manage brick-and-mortar micro-enterprises to provide for their families (Chandy and Narasimhan, 2011). Another focus in the literature is the "technology"-type of entrepreneurs (start-up founders in the high-technology industry). To the extent that the cognitive limitations are widely documented in the population of broadly-defined entrepreneurs, the "technology"-type of entrepreneurs may also benefit from prudence.[35]

Besides the strategic implication that individual entrepreneurs should spend more effort in refining their business ideas, this paper also has policy implications. It shows that entrepreneurs' demand for resources is a function of their cognitive ability. This adds a demand-side perspective to the discussion for addressing entrepreneurs' resource constraints (Bruhn et al., 2010). Resource constraints, particularly in terms of financial assets, remains a critical barrier to entrepreneurship in many economies (e.g. Evans and Jovanovic (1989)). Previous research and policies largely focus on the supply side of the issue. Governments have committed billions of dollars to facilitate lending to small businesses, on the premise that a more entrepreneur-friendly financial system can stimulate innovation and economic growth (e.g. King and Levine (1993); Rajan and Zingales (1998)).[36] This paper adds that whether more generous supply translates into better performance depends on entrepreneurs' cognitive ability. Whereas an increase in resource supply facilitates investing in viable ideas, it also aggravates the hazards of value-destroying investment due to the individuals' inaccurate assessment (Jensen et al., 2014). Policies aimed to address the issue of resource constraints may mitigate the hazards through integrating training or counseling services.[37]

[35] In addition, it is possible that the insights from this paper also apply to managers at larger organizations. This possibility remains to be empirically verified, as managers at larger organizations (e.g. corporate executives) can use more organizational routines or professional consultancy in their decision-making process.

[36] For instance, the U.S. Jumpstart Our Business Startups (JOBS) Act was recently signed into law to provide over 12 billion dollars in loan support for small businesses (U.S. Small Business Administration, 2010b).

[37] This echoes the view in Fafchamps et al. (2011) that the provision of financial capital alone is not enough to boost entrepreneurial success. Note that by highlighting the benefits of training or counseling services, I am not advocating exact replication of the GATE program. The content and the scale of implementation should be subject to more detailed cost-benefit analysis.

Appendix I for Chapter 2: Proof of Propositions 1 and 2

Proposition 1. ***(the Productivity Mechanism):*** $\partial[\pi_A(I_A)]/\partial m > 0$ ***and*** $\partial I_A/\partial m > 0$.

Proof. Define function $F(\cdot) \equiv \partial \pi_A(\cdot)/\partial I$. Then, the first-order condition for the profit-optimization problem requires that

$$F(I_A) = \frac{m\alpha}{1+r} I_A^{\alpha-1} - 1 - C'(I_A - W) \cdot \mathbb{I}(I_A - W) = 0$$

where$\mathbb{I}(\cdot)$ is the index function. By implicit function theorem,

$$\frac{\partial I_A}{\partial m} = -\frac{\partial F(I_A)/\partial m}{\partial F(I_A)/\partial I} > 0.$$

And,

$$\frac{\partial[\pi_A(I_A)]}{\partial m} = \frac{I_A^{\alpha}}{1+r} + F(I_A)\frac{\partial I_A}{\partial m} > 0.$$

□

Proposition 2. ***(the Prudence Mechanism):*** $\partial[\pi_A(I_P)]/\partial \tau < 0$ ***and*** $\partial I_P/\partial \tau > 0$.

Proof. Define function$G(\cdot) \equiv \partial \pi_P(\cdot)/\partial I$. Then, the first-order condition for the profit-optimization problem requires that

$$G(I_P) = m\alpha \frac{1+\tau}{1+r} I_P^{\alpha-1} - 1 - C'(I_P - W) \cdot \mathbb{I}(I_P - W) = 0$$

where$\mathbb{I}(\cdot)$ is the index function. By implicit function theorem,

$$\frac{\partial I_P}{\partial \tau} = -\frac{\partial G(I_P)/\partial \tau}{\partial G(I_P)/\partial I} > 0.$$

And,

$$\frac{\partial[\pi_A(I_P)]}{\partial\tau} = [G(I_P) - \frac{m\tau I^{\alpha}}{1+r}]\frac{\partial I_P}{\partial\tau} < 0.$$

$\square$

Appendix II for Chapter 2: Comparison with Previous Studies Using the GATE Sample

This paper builds on four studies that have analyzed the GATE sample. Two of them focus on the determinants of entrepreneurs' entry decision, and the others are intended as program evaluations from a public policy perspective. Specifically, Michaelides and Benus (2012) find that receiving training motivates the unemployed to enter into entrepreneurship. And Fairlie and Holleran (2012) further show moderation effects by the individuals' attributes. Extending the analysis to a broader range of outcome dimensions, Benus et al. (2009) and Fairlie et al. (2012) find little impact except that GATE is effective in inducing entry by the unemployed in the very short term (within months after the random assignment). Benus et al. conclude that "GATE had no impact on the earnings of the self-employed." (Pp. vi of "Executive Summary"). Fairelie et al. conclude that "Our estimates of average treatment effects across the entire sample suggest that GATE had limited impacts on ultimate outcomes." (Pp. 3).

Those four studies have greatly helped me to understand the experiment and the sample. However, this paper differs from the previous studies in two notable ways.

First, in terms of the purpose, this paper seeks to understand how individual entrepreneurs may improve their businesses through learning. To serve this purpose, I investigate not only the effect of training on the individuals' performance, but also the *mechanisms* whereby that effect channels. The focus of this paper is not on understanding entrepreneurial entry, nor do I intend to provide a comprehensive cost-benefit analysis of the GATE program. And my investigation into the mechanisms, both theoretical and empirical, is not in any of those previous studies.

Second, in terms of the empirics, I present new results related to entrepreneurs' performance, financing and employment that contrast with the non-findings in Benus et al. (2009) and Fairlie et al. (2012). Such difference is due to different empirical approaches, as elaborated below.

Specifically, this paper differs from Benus et al. (2009) mainly in the variables being examined. Benus et al. (2009) measure financial performance by the ratio of revenue over expenses

(Pp. 77), and the count of businesses in each size category (Pp. 108-109). These analyese do not yield statistically significant results . They also examine the financing variables up till the second wave of survey (month 18) (Pp. 87). In contrast, this paper employs more conventional measures, computing net profit as revenue minus expenses and using the raw number of employees. I also investigate the financing of each individual's most recent business, with the majority of the businesses operating after the second wave of survey.

This paper differs from Fairlie et al. (2012) mainly in two ways. The first is the sampling strategy. Fairlie et al. focus on the surviving businesses on the survey date. In their sample, the business-related variables are coded as 0 for closed businesses. This may potentially cause the issue of survivorship bias which eclipses the effects. To overcome this issue, this paper uses the individuals' the most recent business (surviving or closed). I also show that the results hold in both the full sample and the samples conditional on business ownership. Second, the variables and models used in the analyses are also largely different: (1) Instead of analyzing the raw business profit, I take log of all the earnings measures to account for their skewed nature; (2) Fairlie et al. do not examine the entrepreneurs' use of personal loans and own-money financing; (3) In studying the effect on employment size, besides OLS, I also use negative binomial regressions to account for the discrete, non-negative and over-dispersed nature.

Finally, in addition to examining the effects on the variables' mean, as in Benus et al. (2009) and Fairlie et al. (2012), I also study the impact of training on the distribution of the variables. This provides a more fine-grained understanding of the impact. For example, examining the tails of the earnings distribution in Analysis 1 suggests that the performance-boosting effect of receiving training mainly lies in loss prevention.

Chapter 3

Risk Propensity and Financial Returns to Entrepreneurship

Abstract

Entrepreneurship is often associated with risk taking, but the financial implications of entrepreneurs' risk propensity remain elusive. Investigation into this issue is complicated by the close association of risk propensity with the individuals' level of confidence. Drawing on a novel dataset from China, I show that households guided by more risk-tolerant individuals were more likely to enter into entrepreneurship. Entrepreneurs' risk propensity generally is not strongly related to business scale or performance, except that the very risk-tolerant ones tend to have more employees, lower revenue and lower profit. To disentangle risk propensity from overconfidence, I then conduct an experiment where both the traits are explicitly measured. Risk propensity remains negatively associated with business profit even after confidence is controlled for. In summary, this paper highlight the consequences of entrepreneurs indulging in undisciplined risk taking.

"The difference between risk takers and calculated risk takers is the difference between failure and success."

— Len Green, Entrepreneur, Investor and Mentor[1]

3.1 Introduction

Many associate entrepreneurship with a daring act, as the survival and growth of nascent businesses are usually highly volatile.[2] Whereas the entrance to the arena of entrepreneurship seems to demand an appetite for adventures, the link between that appetite and the entrepreneurs' performance remains unclear. Investigation into this link is motivated by the understanding that entrepreneurs' heterogeneity shape their project selection and "management styles"(Bertrand and Schoar, 2003). This investigation not only helps us understand whether risk propensity is a significant determinant of entrepreneurs' performance, but also sheds light on the importance of risk management in market entry and business operations.

The academic discussion on risk propensity and entrepreneurship is mostly focused on the relation between risk propensity and entrepreneurial entry. A string of studies, both theoretical and empirical, generally agree with the intuition that more risk-tolerant individuals tend to select into entrepreneurship (e.g. Kihlstrom and Laffont (1979) and Levine and Rubinstein (2013)). However, the performance implications of entrepreneurs' risk propensity have been less studied. Theoretically, opposite predictions may arise. On the one hand, conventional finance theory predicts that a mean-variance optimizer demands higher expected returns to compensate for a riskier investment (Markowitz, 1952). It follows that entrepreneurs pursuing riskier opportunities tend to have better financial performance on average. On the other hand, risk tolerance increases the hazards of investing in unprofitable projects. This is because in nascent businesses where structured monitoring and advising are often not in place, boundedly rational entrepreneurs may indulge themselves in

[1] Brown (2013).

[2] See Decker et al. (2014) for a recent discussion on the volatility of entrepreneurship, and Audretsch (1991) for a focused discussion on the survival rate of new firms.

undisciplined risk-taking (Simon, 1955; Kahneman et al., 1982). One possibility is entrepreneurs' overconfidence in their relative capabilities (Camerer and Lovallo, 1999). Whereas risk aversion may not correct the cognitive biases *per se*, it protects entrepreneurs by steering them away from projects that they perceive to be too risky, thus mitigating the losses. Therefore, entrepreneurs with greater risk tolerance may perform worse.

The theoretical ambiguity makes an empirical answer all the more desirable. However, the empirical investigation is met with two challenges. First, data scarcity has been a barrier—very few datasets contain information on both the entrepreneurs' risk propensity and their financial returns. Second, the effects of risk propensity may be confounded by other personality traits. In the literature, risk propensity is closely associated with overconfidence, which may cause misperception and also lead to engaging in unprofitable projects(Campbell et al., 2004; Goodie, 2003).

This paper attempts to address the two issues above. The analyses consist of two parts. I first draw on a recently available dataset titled "China Household Finance Survey" (CHFS). CHFS consists of a representative sample of Chinese households in 2011. As the empirical analysis finds, households guided by more risk-tolerant individuals were more likely to own and actively manage a business. In general, I do not find a significant relation between the entrepreneurs' risk propensity and their financial performance, with one exception: the very risk-tolerant entrepreneurs operated larger businesses (measured by the employment size), but had inferior financial performance—their revenue and profit were both lower than the others, even when business size is fixed. The findings are robust to matched sample and correction for selection bias.

Then, to disentangle the effects of risk propensity from overconfidence, I conduct an experiment on an online crowdsourcing platform where both the personality traits are explicitly measured. The experiment consists of two rounds. In the first round, each subject enters a hypothetical scenario where they are launching a new business and need to decide how many employees to hire. The profit added (or subtracted) by each employee is the same, and needs to be randomly determined at the end of the experiment. The subject is informed only of its distribution. The expected value is set to be negative, in order to explain the findings from CHFS. In the second round, each subject enters a similar scenario. The value per employee has the same negative expected value, but it would be determined by the subject's performance in answering 20 business trivia questions at the end of the experiment. The results suggest that the subjects choose to employ significantly more people in the second round than the first. On average, subjects with higher risk tolerance report to be more confident in their performance in the trivia test, though their actual performance does not seem any better than the others. They also have larger employment size and lower business profit, a finding consistent with the CHFS results. The effects of risk propensity remain robust even after controlling for the individuals' level of confidence.

This paper makes two contributions. First, by demonstrating the effects of risk propensity on business scale and profit, it fills a gap in the literature on the performance implications of entrepreneurs' personality traits. In the corporate governance literature, one previous study by Walls and Dyer (1996) examines how managers' risk propensity relates to business profit in established firms. They find an inverse U-shape association in the petroleum exploration industry. However, it remains unclear to what extent can those findings be applied to entrepreneurs in microenterprises. As compared with entrepreneurs in microenterprises, corporate managers are subject to more scrutiny or discipline, but they can also access more resources that may facilitate risk-taking. Therefore, the relation may be more positive or negative in the context of entrepreneurs. This paper provides the first piece of evidence that the profit is lower for the very risk tolerant entrepreneurs.

Second, this paper represents the first step to distinguish the effects of risk propensity from those of overconfidence. These are two distinct concepts that are both elements for computing a project's net present value. Risk propensity refers to the shape of an individual's utility function. The more concave the shape, the more sensitive the individual is to losses relative to gains, thus the more risk-averse the individual is. On the other hand, overconfidence refers to the misperception of the chances—overconfident individuals perceive the chances of favorable outcomes to be higher than the actual ones. Since the two can lead to aggressive behaviors that are often observationally similar, it is difficult to identify the cause without explicitly measuring them. In the experiment, I show that both risk propensity and overconfidence may induce individuals to engage in unprofitable, gambling-like behaviors.

3.2 Risk Propensity and Financial Returns

3.2.1 Context

The hypotheses are tested using data from the China Household Finance Survey (CHFS). This dataset contains over 8,000 households randomly selected from 25 provinces in China in July 2011, and surveys each household for information on its financial asset, business activities and its members' socio-economic conditions (Gan et al., 2014). It is the first nationally representatitve dataset on household finance in China, with sample demographics closely matching those from the National Bureau of Statistics.[3]

CHFS is ideal for the purpose of this paper, in that it includes measures of the individuals' risk propensity and the businesses' scale, revenue and profit. This is uncommon of other datasets. In the statistical analysis, I restrict the sample to urban residents. The rationale is that rural residents are entitled to their land and thus mainly engage in agricultural production. I also exclude households without any members working ("working" defined as being hired by others or self-employed). Inclusion of those households creates an upward bias in our estimation, as they may have opted out of the labor force, possibly due to health conditions, lack of motivation etc. CHFS was conducted in person. In households where there were multiple members, the person that is most familiar with the household's financial situation was selected to respond to the survey. As compared with other members (if any) in a household, the respondent is most likely to guide the financial decisions, as making such decisions requires familiarity with the household's financial situation.

The sample for use has around 4,000 households. Table 3.1 profiles them. These households were distributed more heavily along the coastal provinces, which is economically more advanced. This is consistent with the population distribution of the country. About 60 percent lived in the coastal provinces, a quarter were in the middle of the country, and the rest were located in the

[3] See Page 14, Gan et al. (2014).

further inland region.[4] On average, each household had 3.5 members, of which 0.6 is under the age 16. 80 percent of the households had at least one member employed by others. About a quarter of the sample housed communist party members. And in 9 percent of the households, at least one member was hired by others to lead a communist, commercial or social-service organization.[5] In terms of social exchange, half of the sample received gifts worth more than 100 RMB[6] from non-family members, and almost 80 percent of the sample sent gifts to non-family members. The value of the households' assets averaged 656,000 RMB, where the assets may include cash, financial securities, real estate, automobiles, cars and valuable commodities such as jewelries.[7]

In the sample, 17 percent of the households engaged in entrepreneurship. A household's entrepreneuial entry is defined by: 1) owning a stake in a business; and 2) having at least one member who is actively managing the business.

The table also summarizes the characteristics of the respondents, that is, the people most familiar with their households' financial situation. On average, the respondents were about 44 years of age. Half of them were male. The vast majority were married. Almost half did not finish high school, and 14 percent had a college degree or above.

A key variable for the analysis is risk propensity. Early in the survey and before the questions on financial assets and business performance, each respondent was asked the following question: "Suppose you have financial capital to invest, which type of the following projects would you like to invest in?" The respondent was asked to select one of the following: 1) "projects with high risk and high returns;" 2) "projects with moderately high risk and moderately high returns;" 3) "projects

[4]In the CHFS survey, the coastal region includes the following provinces or municipalities: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Shandong and Guangdong. The middle region includes Hunan, Hubei, Henan, Jiangxi, Anhui and Shanxi. The further inland region includes Qinghai, Gansu, Yunnan, Sichuan, Chongqing, Heilongjiang and Jilin.

[5]In China, the communist organizations ("*Dang Qun Zu Zhi*") are the party-controlled units that exist at various levels (e.g. municipal, within a firm, within a class at school). Each of them may take on a specific function, such as propoganda, labor relation and party membership. The commercial organizations ("*Qi Ye Dan Wei*") refer to for-profit enterprises, public or private. In contrast, the social-service organizations ("*Shi Ye Dan Wei*") are non-for-profit. Each of them also serves a specific purpose, such as propoganda, education, social work etc. They also operate at various levels (e.g. municipal, residential block) and usually under the supervision of a higher-level communist or governmental organization.

[6]At the time of the survey, one US dollar roughly equals 6.4 RMB.

[7]To address the influence of outliers, the value of the asset is winsorized at 1 percent at both tails.

with average risk and average returns;" 4) "projects with moderately low risk and moderately low returns;" 5) "I would like to bear no risk at all." Based on this measure, I classify the respondents into three categories. Those selecting 1) and 2) are classified as "most risk-tolerant," those selecting 3) are labeled "moderately risk-tolerant," and the others "least risk-tolerant."[8] As shown in the table, over half of the respondents were relatively risk-averse, 30 percent of them were "moderately risk tolerant," and 17 percent were "most risk-tolerant."

The self-reported psychometric measure of risk propensity are common in the literature (e.g. Ekelund et al. (2005); Naldi et al. (2007); Willebrands et al. (2012)). It has also been shown to be closely related to experimentally-determined risk measures (Dohmen et al., 2011).

Table 3.2 profiles the households' businesses. Their average age was 7.8 years. Almost 90 percent were proprietorship. In contast, 5 percent were partnership, 5 percent were limited-liability corporations, and only 3 percent were listed companies. About 40 percent of the businesses employed people outside the household. The average number of employees is 13.9. In terms of financial performance, the businesses had an average revenue of about 229,000 RMB the year prior to the survey. The average amount of profit is about 44,000 RMB.[9]

Table 3.3 illustrates the industry distribution. Over 40 percent of the businesses dealt with whole sale or retail trade. The next most popular industry category is accommodation and restaurants, which accounts for 12 percent. Manufacturing and residential services respectively account for 8 percent.

3.2.2 Model

In the main analysis, I test the hypotheses using the following model:

$$E(y_i|Most_i, Mod_i, \mathbf{X_i}) = \alpha + Most_i \cdot \beta_1 + Mod_i \cdot \beta_2 + \mathbf{X_i} \cdot \gamma$$

[8] Note that this classification scheme sorts the respondents by their relative risk propensity in the sample, but makes no assumption on the absolute risk propensity of the "most risk-tolerant" category. It is possible that a respondent in this category was risk-averse, risk-neutral or risk-seeking.

[9] The revenue and the profit are winsorized at 1 percent at both tails.

Table 3.1: Profile of All Households

	mean	st. dev	N
Household Characteristics			
Geographic Region:			
Coastal Provinces	0.57	0.49	4075
Middle Provinces	0.26	0.44	4075
Western Provinces	0.17	0.38	4075
Number of Members	3.49	1.35	4075
Number of Children (< 16 Years)	0.56	0.69	4075
Any Salaried Worker in Household	0.80	0.40	4075
Any Communist in Household	0.26	0.44	4035
Any Member Hired to Lead a Communist/Commercial/Social Organization	0.09	0.29	4075
Any Gift Received from Non-Family Last Year	0.50	0.50	4068
Any Gift Sent to Non-Family Last Year	0.79	0.41	4069
Household Asset (1000 RMB)	656.07	974.88	4075
Entry into Entrepreneurship	0.17	0.37	4074
Person Most Familiar with the Household's Finance			
Age (Years)	43.59	12.70	4075
Sex (Male = 1)	0.49	0.50	4075
Marital Status			
Single	0.07	0.26	4039
Married/Cohabitation	0.87	0.34	4039
Others	0.06	0.24	4039
Educational Level			
Junior High School or Below	0.48	0.50	4042
High School	0.39	0.49	4042
College or Above	0.14	0.34	4042
Risk Propensity			
Most Tolerant	0.17	0.37	4027
Moderately Tolerant	0.30	0.46	4027
Least Tolerant	0.53	0.50	4027

Table 3.2: Profile of the Households' Businesses

	mean	st. dev	N
Business Age (Years)	7.78	6.49	669
Legal Structure:			
Listed Company	0.03	0.17	674
Limited-Liability Corporation	0.05	0.22	674
Partnership	0.05	0.22	674
Proprietorship	0.87	0.33	674
Had Any Employee	0.38	0.48	669
Number of Employees	13.87	135.39	669
Revenue (1000 RMB)	229.93	676.86	596
Profit (1000 RMB)	44.73	89.87	615

Table 3.3: Industry Distribution of the Households' Businesses

Industry No.	Industry Name	N	%
1	Mining	6	0.89
2	Manufacturing	57	8.47
3	Production and Distribution of Electricity, Gas and Water	5	0.74
4	Construction	39	5.79
5	Transportation, Logistics and Postal Services	30	4.46
6	Information Transfer, Computer Services and Software	18	2.67
7	Whole Sale and Retail Trade	281	41.75
8	Accommodation and Restaurants	80	11.89
9	Finance	2	0.30
10	Real Estate	6	0.89
11	Leasing and Business Services	27	4.01
12	Scientific Research, Technical Services and Geological Survey	1	0.15
13	Management of Water Conservancy, Environment and Public Facility	3	0.45
14	Resident Services and Other Services	56	8.32
15	Education	3	0.45
16	Sanitation, Social Security and Social Welfare	8	1.19
17	Culture, Sports and Entertainment	18	2.67
18	Public Administration and Social Organization	0	0.00
19	International Organizations	0	0.00
20	Others	33	4.90

where y_i denotes the dependent variable of interest for household i. $Most_i$ is a dummy variable for the respondent being "most risk-tolerant" in the sample, and Mod_i is a dummy for being "moderately risk-tolerant." Thus the coefficient $\beta_1(\beta_2)$ captures the difference between the "least risk-tolerant" and the "most risk-tolerant" ("moderately risk-tolerant") respondents. $\mathbf{X_i}$ is a vector of control variables. Specifically, in all the regressions, the control variables consist of the following: 1) demographics, including the number of household members, the number of children (younger than 16 years), whether household had salaried worker, the amount of household asset (log), the perceived level of neighborhood safety, the respondent's age, square of age, sex, marital status and province fixed effects; 2) human capital, including dummies for the respondent's educational level; and 3) social capital, including whether the household had communist party member, whether the household had a leader of a communist/commercial/social organization, whether the household sent any gift worth more than 100 RMB to non-family members, and whether the household received any of such gift from non-family members. When the dependent variable relates to business employment or performance, $\mathbf{X_i}$ also consists of a set of business characteristics, including business age, legal structure and industry fixed effects. When the dependent variable relates to business performance, $\mathbf{X_i}$ also includes the employment size.

To correct for potential selection bias in estimating the effect on business employment or performance, I employ Heckman selection model. The Heckman model aims to address the households' selection into entrepreneurship. The underlying reduced-form model is specified as below:

$$y_i = \alpha + Most_i \cdot \beta_1 + Mod_i \cdot \beta_2 + \mathbf{X_i} \cdot \gamma + u_i$$

where u_i is the error term and the other variables as the same as specified above. We would like to estimate the β's for the entire sample, however, the business outcome variables are observed only for people self-selected into entrepreneurship. This creates a potential selection bias. To address this issue, we specify a two-stage Heckman model, where the first stage models the households' decision to enter entrepreneurship:

$$I_i^* = \delta + \mathbf{X_i} \cdot \theta + \varepsilon_i$$

$I_i^*$is a continuous variable denoting a household's propensity towards entrepreneurship. A household enters entrepreneurship if and only if I_i^*> 0. The second stage models the business outcome conditional on entrepreneurial entry:

$$E[y_i | I_i^* > 0] = \alpha + Most_i \cdot \beta_1 + Mod_i \cdot \beta_2 + \mathbf{X_i} \cdot \gamma + \eta \cdot \lambda_i$$

Under the joint-normal assumption of ε and u, the selection bias can be corrected by inserting λ, the inverse mills ratio computed from the first stage. One caveat of this approach is that without an IV, the coefficients of the first stage may not be consistently estimated. Nontheless, this approach is still widely used in economics and finance (e.g. Fang (2005)).

In addition, as a robustness check, I also employ propensity score matching to construct a more balanced sample. This allows comparison with the results from the main analysis, and informs of the extent to which the observed effects are driven by the unobserved factors.

3.2.3 Empirical Results

Table 3.4 presents the regression results for entrepreneurial entry. The coefficient estimates remain qualitatively similar as more control variables are added. The entry rate signficantly increases with the respondents' risk tolerance. In an untabulated estimate, the average respondent's entry rate increases by about two (four) percentage points if she changes from being "least risk-tolerant" to "moderately (most) risk-tolerant." The magnitude of the effect is not trivial, as compared with the entry rate of 17 percent for the sample.

In Table 3.5, the results suggest that more risk-tolerant entrepreneurs tend to operate larger businesses. On average, the likelihood of having any employees increases by about 9 percentage points if a "least risk-tolerant" entrepreneur changes to "moderately risk-tolerant," and the likeli-

Table 3.4: Coefficients for Regressions: Entrepreneurial Entry

DV: Binary Indicator for Household Engagement in Entrepreneurship			
	(1)	(2)	(3)
	Logit	Logit	Logit
Dummy: Most Tolerant	0.407***	0.439***	0.403***
	(0.144)	(0.145)	(0.146)
Dummy: Moderately Tolerant	0.211*	0.224*	0.220*
	(0.116)	(0.116)	(0.116)
Constant	Yes	Yes	Yes
Control: Demographics	Yes	Yes	Yes
Control: Human Capital	No	Yes	Yes
Control: Social Capital	No	No	Yes
Log Likelihood	-1360.60	-1357.30	-1342.25
N	3987	3987	3973

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. White standard errors are presented in brackets.

hood increases by 15 percentage points if she changes to "most risk-tolerant." When measured by the number of employees, businesses run by the "moderately risk-tolerant" ("most risk-tolerant") entrepreneurs tend to be 21 (44) percent larger than those run by the "least risk-tolerant."

Table 3.5 also presents the estimated effects on financial performance. When employment size and other aforementioned control variables are fixed, the "most risk-tolerant" entrepreneurs achieve significantly less profit and less revenue than the "least risk-tolerant" ones. The difference is 27,982 RMB (or 31% of the sample standard deviation) for profit and 126,000 RMB (or 31% of the sample standard deviation) for revenue. However, "moderately risk-tolerant" entrepreneurs were not significantly different from the "least risk-tolerant." This seems to suggest a concave shape of the effect on financial performance.

3.2.4 Robustness Checks

To test the face validity of the risk propensity measure, I conduct a set of regressions to see how well the measure predicts the households' engagement in risky activities. The model is the same as in the main analysis. The results, as presented in Table 3.6, suggest that the more risk-tolerant

Table 3.5: Coefficients for Regressions Using Heckman Two-Stage Model

	(1) DV (Binary): Had Any Employee	(2) DV: Number of Employees (Log)	(3) DV: Profit (1000 RMB)	(4) DV: Revenue (1000 RMB)
Second Stage:				
Dummy: Most Tolerant	0.151**	0.447**	-27.982**	-207.477**
	(0.068)	(0.182)	(13.058)	(102.141)
Dummy: Moderately Tolerant	0.096**	0.216*	-0.238	-72.500
	(0.047)	(0.127)	(9.445)	(74.308)
Number of Employees (log)			10.628***	209.066***
			(3.550)	(26.111)
Inverse Mills Ratio	0.318	1.494*	-58.356	-567.116
	(0.320)	(0.789)	(62.672)	(482.433)
Constant	Yes	Yes	Yes	Yes
Control: Business	Yes	Yes	Yes	Yes
Control: Demographics	Yes	Yes	Yes	Yes
Control: Human Capital	Yes	Yes	Yes	Yes
Control: Social Capital	Yes	Yes	Yes	Yes
First Stage:				
Dummy: Most Tolerant	0.236***	0.233***	0.220***	0.224***
	(0.079)	(0.079)	(0.082)	(0.082)
Dummy: Moderately Tolerant	0.112*	0.110*	0.116*	0.126*
	(0.066)	(0.066)	(0.068)	(0.068)
Constant	Yes	Yes	Yes	Yes
Control: Demographics	Yes	Yes	Yes	Yes
Control: Human Capital	Yes	Yes	Yes	Yes
Control: Social Capital	Yes	Yes	Yes	Yes
N	3965	3965	3914	3897

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. White standard errors are presented in brackets.

Table 3.6: Coefficients for Regressions: Risky Engagement

	(1)	(2)	(3)
	Logit	Logit	Logit
	DV (Binary): Own Any Risky Asset	DV (Binary): Had Revenue from Lottery	DV (Binary): Had Revenue from Gambling
Dummy: Most Tolerant	1.061***	1.147**	1.077***
	(0.133)	(0.463)	(0.383)
Dummy: Moderately Tolerant	0.369***	0.648	1.104***
	(0.124)	(0.479)	(0.341)
Constant	Yes	Yes	Yes
Control: Demographics	Yes	Yes	Yes
Control: Human Capital	Yes	Yes	Yes
Control: Social Capital	Yes	Yes	Yes
Log Likelihood	-1288.12	-186.90	-291.74
N	3974	3507	3599

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. White standard errors are presented in brackets.

the respondent was, the more likely her household was to invest in risk assets (including stocks and financial derivatives), to have revenue from lottery, and to have revenue from gambling. The results lend confidence to using the self-reported risk propensity measure.

Despite the fact that the regressions control for a rich set of variables, it is still possible that the effect is confounded by unobserved factors. One possibility is that the negative association between risk propensity and entrepreneurial performance is driven by unobserved ability—risk-averse people might be "smarter" or better at managing a business. However, this alternative explanation is not consistent with the evidence in the literature that risk aversion tends to be associated with lower IQ (Dohmen et al., 2010).

To more systematically address the potential endogeneity issue, I run the regressions above using weights constructed from propensity scores (Imbens, 2004; Rawley and Simcoe, 2010; Caliendo and Kopeinig, 2008). This weighted approach constructs an observationally more similar ("balanced") sample. It builds on the "conditional independence" assumption: the households with the same propensity score would have the same outcome distribution if they have the same risk propensity (Rosenbaum and Rubin, 1983). This approach proceeds as follows. First, because this approach applies to dichonomous group comparison, I first define the "most risk-tolerant" households as the treatment group, and the rest of the sample as the control group. Second, I run a probit regression using the model in the main analysis, with the dependent variable being a binary indicator of belonging to the treatment group. The predicted likelihood is the propensity score. Only the observations that fall in the common score range ("common support") of both groups are kept. For the treatment group, the sample weight for each observation is defined to be the inverse of the propensity score; for the control group, the weight is the inverse of one minus the propensity score.[10] Finally, I run the regressions in the main analysis with the weights.

Table 3.7 presents the results. In general, the effects are qualitatively similar to those from the main analysis: the "most risk-tolerant" entrepreneurs had larger business scale and worse financial performance. The magnitude of the effect is very similar to the one in the main analysis for entrepreneurial entry, business profit and revenue. This helps mitigate the concern about endogeneity.[11]

3.3 Risk Propensity or Confidence?

3.3.1 The Experiment

As mentioned earlier, the effects of risk propensity are difficult to disentangle from overconfidence without explicit measures of both. The conditional independence assumption, on which the above propensity-score weighted regressions are based, may not hold given the close association between risk propensity and overconfidence. Next, I conduct an experiment to find out the drivers of the results from the CHFS sample.

[10]See Imbens (2004) for a formal poof. Intuitively, by applying the sample weights as stated, the treatment-group observations with a lower propensity score gets assigned larger weights, thus the weighted treatment group looks more similar to the control group than the unweighted one. Similarly, the weighted control group looks more similar to the treatment group.

[11]The effects on the business scale become weaker in the weighted regressions. This is possibly due to the exclusion of observations outside the common support.

Table 3.7: Average Treatment Effect Using Propensity Score Weighting

	(1)	(2)	(3)	(4)	(5)
	Logit	Heckman	Heckman	Heckman	Heckman
	Binary: Entry	Binary: Had Any Employee	Number of Employees (Log)	Profit (1000 RMB)	Revenue (1000 RMB)
Dummy: Most Tolerant	0.400**	0.173*	0.415	-33.904**	-279.745**
	(0.161)	(0.100)	(0.289)	(14.924)	(134.865)
Number of Employees (log)				9.318*	205.767***
				(5.592)	(70.420)
Inverse Mills Ratio		0.738	1.706	-102.803	-1288.305
		(0.576)	(1.719)	(84.365)	(855.604)
Constant	Yes	Yes	Yes	Yes	Yes
Control: Business	No	Yes	Yes	Yes	Yes
Control: Demographics	Yes	Yes	Yes	Yes	Yes
Control: Human Capital	Yes	Yes	Yes	Yes	Yes
N	3917	652	652	602	585

Notes:

(1) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(2) The Heckman results are for the second stage. Both stages are weighted.

(3) Column (1) presents White standard error in parentheses. Columns (2)-(5) present Jacknife standard errors.

The experiment was conducted on Amazon Mechanical Turk ("M-Turk"), an online crowd-sourcing platform with increasing popularity for academic research. As compared with the lab, M-Turk offers the advantages of faster recruitment and lower costs (Mason and Suri, 2012). There are around 100,000 registered workers on M-Turk in 2007(Pontin, 2007), and that number has grown to 500,000 in 2014.[12] The effective hourly wage averages 4.8 U.S. dollars (Ipeirotis, 2010).

I advertised the experiment in July 2015, with a plan to recruit 800 subjects. The access to the advertisement was restricted to those self-reported to be based in the U.S., have completed at least 100 tasks and have an approval rate of at least 95 percent. The advertisement invited the subjects to complete "20 business trivia questions and some simple tasks." It also explicitly told them that their payment depended on their performance and that "all the participants are recruited on Mechanical Turk and are shown the same information above." The sample for use contains 691 individuals, after I remove submissions with duplicate IP addresses or M-Turk worker IDs and the ones that spent less than 10 seconds in either of the "business launching" rounds (see the description below about the "second part" of the experiment).

For each subject, the experiment proceeded in the order of the following four parts. The first part used the "lottery" approach in Holt and Laury (2002) to assess the subject's general risk propensity. Specifically, on each separate page, the subject was asked to choose between a pair of alternatives — "receiving a fixed amount of money for sure" and "receiving 50 cents with 50% chances and 0 cent with 50% chances." Across the pages, the fixed amount increased from 0, 2, 5, 10, 15, 20, 25, 30, 35, 40, 25 to 50 cents, whereas the other alternative remained the same. If the subject chose to receive the fixed amount at any page, this part was over. Otherwise, the fixed amount kept increasing until it reached 50 cents. This lottery approach thus characterizes the subject's risk attitude using the fixed amount at which she switched from a risky to a safe alternative. To make her choice incentive compatible, the subject was shown a message at the start stating that one of her choices would be randomly selected and that her selection in that choice would determine her payoff for this part. This approach has been widely used in economic

[12] https://requester.mturk.com/tour. Accessed August 10th, 2015.

experiments. It measures the subject's general attitude towards financial risks rather than risk propensity specific to an entrepreneurial setting.

In the second part, all the subjects were randomly assigned to one of two groups: "control" and "treatment". Each subject in the control group went through two rounds individually. The first round was the "random" round. The subject entered into a hypothetical situation where she was launching a business. She may choose to have 0, 1, 2, 3, 4 or 5 employees. If she did not have any employees, her business profit was 10 cents. The profit created by each employee was the same but currently unknown. It was to be randomly determined at the end of the experiment. With 20 percent chances, each employee would add two cents to the profit; with 80 percent chances, each employee would subtract two cents from the profit. The subject was then asked how many employees she would like to have. The random round serves the purpose of assessing the subject's risk propensity specific to an entrepreneurial context. Because the purpose of this online experiment is to identify the reasons for the association between high risk tolerance and low profit, which is a finding from the archival data above, this experiment sets the expected value of an employee to be negative in order to focus on the subjects with high risk tolerance.The second round, termed the "skill" round, presented the subject with a similar situation to the first round, except for an important difference: the profit created by each employee would not be determined randomly, but rather by the subject's performance in answering 20 business trivia questions at the end of the experiment (Camerer and Lovallo, 1999). If the subject was among the 20 percent of all subjects that answered the most questions correctly, each of her employee would add two cents to her profit; otherwise, each employee would subtract two cents from her profit. The subject was explicitly informed that all the participants in the study "are reading the same content" for this round. Besides her choice of the number of employees, the subject was also asked to indicate, using percentage points, how confident she thought she would be among the top 20 percent performers. The subject's payment in this part was the combined business profits from both rounds.

The "random" and "skill" rounds differ only in how much control the subject had over the returns to risk taking. As the probabily distribution of the returns (*i.e.* the profit per employee) is known and objective, the level of confidence does not play a role in the subject's decision making. In contrast, in the "skill" round, the profit per employee is a function of the subject's performance in the trivia questions. Thus the subject's decision is driven by the self-assessment of her ability.

The treatment group members went through very similar "random" and "skill" rounds, except in each round they were shown a "risk warning" message. The message was highlighted in bold, red font, and read "Beware the risks here. Having more employees may potentially cause a greater loss of profit. It is possible that all your payoff on this page will be wiped out."

The third part of the experiment collected each subject's demographic information. Finally, the fourth part consisted of 20 business trivia questions. All the questions were timed according to their length. If time was up for one question, the next would automatically replace the current one. The imposition of time limit was aimed to reduce the likelihood of cheating (e.g. searching answers using the internet).[13] The subjects' final payment was the sum of the following: a 30-cent base, payoff from the first part and the combined business profits from the second part.

3.3.2 Analysis of Experiment Data

A general profile of the subjects and their choices in the two rounds is presented in two tables and one figure below. As in Table 3.8, on average, the subjects employ more for their business in the skill round, where the profit per employee is determined by the entrepreneurs' performance, than in the random round, where the profit per employee is out of the entrepreneurs' control. However, the relative aggression in the skill round does not seem to be motivated by correct self-assessment, as the average business profit is significantly lower in the skill round than in the random round. Table 3.9 summarizes the characteristics of the sample by the selected number of employees in the random round. Perhaps unsurprisingly, the group choosing 0 employee in the random round has the largest size, as it contains people that are not on the risk-tolerant end of the spectrum.

[13] In addition, the instructions at the start of this experiment asked the subjects to "answer all the questions without the help of others or any device." I do not find evidence that suggests cheating being prevalent in the sample. The answers to most of the 20 trivia questions used should be pretty easy to find out using internet searching engines. However, of the 691 subjects, the mean and median number of correct questions are around eight. And it took only 12 correct answers for one to rank the top 10 percent.

Table 3.8: The Random vs. Skill Round

	Random Round			Skill Round			p-Value for
	Mean	St. Dev.	N	Mean	St. Dev.	N	Paired t-test
Employment Size	1.65	1.48	691	2.27	1.73	691	0.00
Profit	8.01	3.97	691	7.15	4.95	691	0.00

From this table, the risk propensity in the entrepreneurial context seems to be positively correlated with the general attitude towards financial risks. In addition, the risk propensity is also related to self-assessment of the performance in the trivia test. The more employees one chooses in the random round, the more confident she reports to be. We also observe that the more risk-tolerant subjects choose more employees in the skill round, but end up with lower profit. From the statistics, neither the confidence nor selected employment size seems to be positively related with the actual performance in the trivia test. Figure 3.1 echos the association of risk propensity with confidence, employment size and profit. It further suggests that the association does not seem to differ significantly between the treatment and the control groups.

The regression coefficients in Table 3.10 suggest that both risk tolerance and confidence may drive the larger employment size and lower profit. On the right hand side, the variables of main interest are the treatment group indicator, the risk propensity dummies (proxied by the number of employees selected), and the interaction terms between them. Columns (1)-(3) confirm the findings that more risk tolerant subjects tend to be more confident in the skill round, choose more employees and attain lower profit. Columns (4) and (5) add the individuals' level of confidence as a right-hand-side variable. Similar to risk propensity, confidence is positively related with employment size and negative related with profit. Meanwhile, the coefficients of the risk-propensity dummies remain qualitatively unchanged, except for a slight decrease in magnitude.[14]

The risk warning message that appeared exclusively for the treatment group did not seem to have a strong impact. In Table 3.10, the coefficients of the interaction terms between the risk-

[14] All columns control for the individuals' sex, age, whether born in the U.S., race, education, current employment status, marital status, number of children, household income, startup experience and the number of trivia questions correctly answered. Columns (2) and (4) employ ordered logit to address the censorship issue of employment size. The results in those columns are similar under OLS.

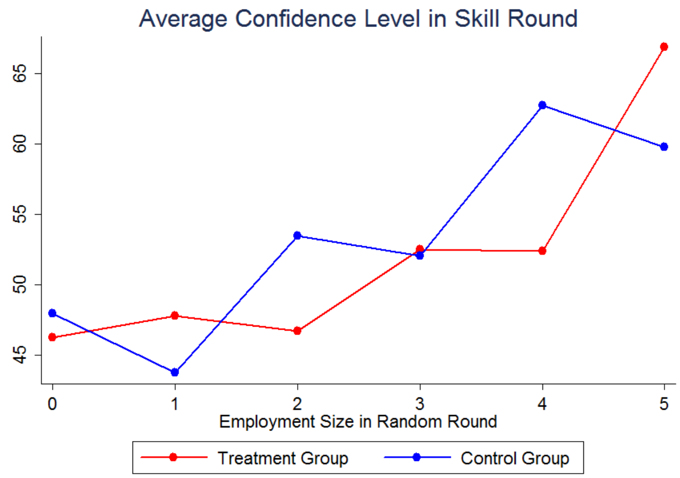
Table 3.9: Sample Characteristics by Risk Propensity

	Employment Size in Random Round					
	0	1	2	3	4	5
% Risk-Seekers (Defined by Lottery Experiment)	29.78	33.71	32.29	34.19	43.48	48.88
Skill-Round Confidence (Percentage Points)	47.23	46.12	49.68	52.26	59.13	62.13
Skill-Round Employment Size	1.60	1.78	2.23	2.92	3.65	4.33
Skill-Round Profit	8.88	8.02	6.71	6.10	4.96	2.49
Number of Questions Answered Correctly	8.68	8.19	7.86	7.65	8.26	7.53
% Males	53.78	24.72	33.85	41.03	34.78	46.67
Age (Years)	39.07	39.79	36.95	37.14	39.00	40.80
% Born in the U.S.	94.67	94.38	96.35	94.87	95.65	95.56
% Hispanic	4.44	5.62	5.73	5.13	8.70	6.67
% Asian	6.67	1.12	4.69	7.69	0.00	2.22
% Black	8.44	5.62	8.85	6.84	8.70	8.89
% White	78.67	86.52	77.60	77.78	82.61	80.00
% Having High School Diploma or Some College	38.22	43.82	50.00	51.28	56.52	46.67
% Having College Degree	37.33	38.20	32.81	34.19	34.78	40.00
% Having Attended Graduate School	23.56	16.85	16.67	14.53	8.70	11.11
% Currently Employed	72.44	76.40	67.19	78.63	91.30	71.11
% Household Income < 50,000 USD	57.78	52.81	52.60	47.01	34.78	35.56
% Household Income Between 50,000 and 99,999 USD	30.22	28.09	32.29	40.17	39.13	55.56
% Household Income Between 100,000 and 149,999 USD	9.33	12.36	11.46	7.69	17.39	6.67
% Startup Experience	25.33	26.97	21.35	34.19	30.43	40.00
% Single	43.56	34.83	37.50	35.90	26.09	28.89
% Married	45.78	52.81	56.25	50.43	60.87	57.78
Number of Children	1.00	0.99	1.05	1.15	1.48	1.27
N	225	89	192	117	23	45
Percentage of Sample	32.56	12.88	27.79	16.93	3.33	6.51

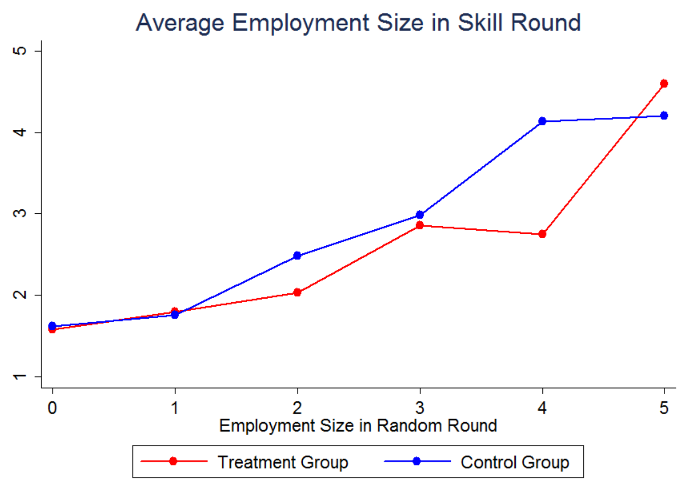
Notes: The numbers are the means. For clarity of presenation, the standard errors are not tabulated but available upon request.

Figure 3.1: Confidence, Employment and Profit by Risk Propensity

(a)



(b)



(c)

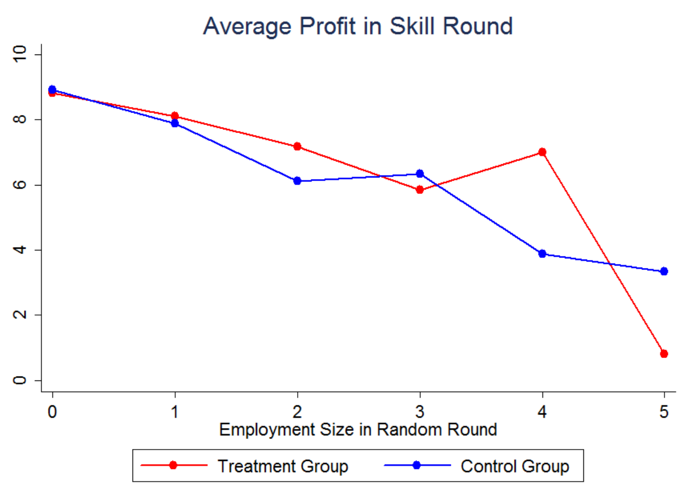


Table 3.10: Regressions of Skill-Round Confidence, Employment and Profit

	(1)	(2)	(3)	(4)	(5)
	OLS	Ordered Logit	OLS	Ordered Logit	OLS
	Confidence Level	Employment Size	Business Profit	Employment Size	Business Profit
Dummy Predictors:					
Treatment	-1.285	-0.020	-0.260	-0.072	-0.293
	(4.272)	(0.413)	(0.570)	(0.360)	(0.554)
(1) Random-Round Employment = 1	0.000	0.832**	0.011	0.807*	0.011
	(4.964)	(0.366)	(0.729)	(0.423)	(0.689)
(2) Random-Round Employment = 2	7.485*	1.654***	-2.387***	1.376***	-2.194***
	(3.822)	(0.381)	(0.438)	(0.345)	(0.429)
(3) Random-Round Employment = 3	5.792	2.270***	-2.182***	2.245***	-2.033***
	(3.849)	(0.431)	(0.649)	(0.434)	(0.657)
(4) Random-Round Employment = 4	16.056***	3.739***	-4.792***	3.541***	-4.379***
	(5.125)	(0.388)	(1.087)	(0.439)	(0.965)
(5) Random-Round Employment = 5	13.965**	4.079***	-4.669***	3.865***	-4.310***
	(5.729)	(0.593)	(0.915)	(0.664)	(0.965)
Interaction Terms:					
(1) $\times$Treatment	2.796	-0.134	-0.829	-0.160	-0.757
	(6.131)	(0.504)	(1.156)	(0.461)	(1.128)
(2) $\times$Treatment	-4.393	-0.443	1.711*	-0.195	1.598*
	(4.968)	(0.457)	(0.867)	(0.432)	(0.858)
(3) $\times$Treatment	1.974	-0.085	0.444	-0.151	0.495
	(6.525)	(0.496)	(0.932)	(0.442)	(0.890)
(4) $\times$Treatment	-4.413	-1.826***	2.839	-1.899***	2.725
	(10.685)	(0.684)	(2.559)	(0.548)	(2.554)
(5) $\times$Treatment	5.662	0.667	-2.015*	0.758	-1.870*
	(9.017)	(0.772)	(1.101)	(0.737)	(1.080)
Skill-Round Confidence				0.046***	-0.026***
				(0.004)	(0.005)
Constant	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-sq	0.151		0.411		0.425
Log Likelihood		-1041.838		-948.154	
N	691	691	691	691	691

Notes:

(1) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(2) Standard Errors are presented in parentheses. They are clustered by the state.

Table 3.11: Regressions Testing the Average Treatment Effects

	(1)	(2)	(3)	(4)	(5)
	Ordered Logit	OLS	OLS	Ordered Logit	OLS
	Random-Round Employment	Random-Round Profit	Skill-Round Confidence	Skill-Round Employment	Skill-Round Profit
Dummy: Treatment	-0.048	0.042	-2.105	-0.259	0.328
	(0.167)	(0.280)	(2.341)	(0.184)	(0.332)
Constant	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-sq		0.127	0.120		0.329
Log Likelihood	-1034.478			-1141.443	
N	691	691	691	691	691

Notes:

(1) * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(2) Standard Errors are presented in parentheses. They are clustered by the state.

propensity dummies and the treatment group indicator are generally not statistically significant, echoing the observation in Figure 3.1. Table 3.11 summarizes a separate set of regressions that test the effects of the risk warning message. In terms of the employment size and profit in both rounds and the confidence in the skill round, there is no statistically significant difference between the treatment and the control groups. As a potential explanation for the lack of the effect, the control group subjects may have warned themselves when reading the scenario description, even though they did not receive an explicit message about the risks.[15]

3.4 Conclusion

In general, I show that entrepreneurs' risk propensity is only weakly linked to their business profit. This may reflect the opposing effects of pursuing higher-risk, higher-return projects versus engaging in gambling-like investments. One important exception is the extreme risk takers: for the

[15] In addition, the lack of treatment effects is unlikely due to insufficient attention. Given its bold and red font, the risk warning message was hard to ignore visually. If the subjects did not pay attention to the scenario description, it would be difficult to explain why the employment size, profit and confidence vary with risk propensity.

very risk tolerant entrepreneurs, they tend to pursue greater scale but suffer from lower profit than others. The findings are robust to controlling for the individuals' level of confidence.

The results have implications for entrepreneurs conducting better risk management. As compared with established, mature businesses, nascent ventures often operate under a more limited amount of resources. This implies lower ability to buffer the losses from a failed investment. It is therefore advisable for entrepreneurs to fully appreciate the consequences before taking on risky investments.

There are several limitations about the online experiment and using multiple methods in this paper. First, whereas M-Turk has the advantage of low cost and time efficiency, it remains unclear how generalizable the results are to settings where the financial stakes are higher and the decision-making takes more time. Second, in the online experiment, the level of confidence is measured using a self-reported percentage. This measure may not be incentive compatible, and is subject to reporting errors. Third, although the results of the online experiment are consistent with the findings from the archival data, it is not entirely clear to what extent they share the same mechanisms. With these caveats in mind, the results from this paper should be interpreted carefully. Nontheless, they represent a step forward towards understanding the performance implications of entrepreneurs' risk propensity. Future work may benefit from incorporating more fine-grained and incentive compatible measures into their study design.

Chapter 4

With a Little Help of My (Former) Employer: How Entrepreneurs Benefit From Working at Prominent Companies?[1]

Abstract

Spawns, or new ventures founded by former employees at prominent companies, have been documented to enjoy greater chances of success. However, it remains unclear whether this is due to selection on the labor market or inherited human/social capital. It is also not clear what entrepreneurial abilities prominent companies help to develop. Using a sample of U.S. technology startups, we show the following: (1) Spawns are more likely to get acquired or become public and more likely to secure early-stage financing. Their advantages remain robust to the use of instru-

[1]This chapter is coauthored with Michael (Zhan) Shi, assistant professor at Arizona State University. Email: zmshi@asu.edu.

mental variable—the proportion of new hires accounted by prominent companies in the industry-year the founders started working. (2) Compared with ventures spinned out from non-prominent companies, spawns have an advantage only if they operate in a business similar to their founders' former employers. (3) Prominent employers mainly prepare entrepreneurs for managing their ventures rather than timing the market. The findings have implications for new ventures' strategy and individuals' career choice.

4.1 Introduction

Spawns refer to business startups founded by former employees at prominent companies. As compared with other startups, they have been documented to enjoy greater likelihood of success. In a recently published overview of 10 years' investments, the venture capital firm First Round Capital hails the spawns' outstanding performance:

> Teams with at least one founder coming out of Amazon, Apple, Facebook, Google, Microsoft or Twitter, performed 160% better than other companies. And while school didn't have any real impact on pre-money valuations, company alma maters did. Founding teams with experience at any of those marquee companies landed pre-money valuations nearly 50% larger than their peers. We have some theories about causation here: the impact of embedded networks, foundational skills these types of jobs provide. These factors clearly make a difference.[2]

Consistent with the testimony above, existing academic research typically attributes spawns' superior performance to the human and social capital inherited from their former employers (e.g. Agarwal et al. (2004); Chatterji (2009)). Whereas it is tempting to think that working for prominent companies prepares the aspiring entrepreneurs with useful skills and networks, this argument is complicated by the possibility that prominent companies select employees who happen to have better entrepreneurial abilities. Without ruling out this possibility, it would be premature to establish prior employers as a source of entrepreneurs' competitive advantage.

This paper aims to take a step forward towards understanding the determinants of spawns' performance. Our research question is: does working for a prominent company subsequently benefit the entrepreneurs, and if so, how? There could be many ways to answer the "how" part. In this paper, we focus on what entrepreneurial abilities do the prominent employers help to develop.

Our theoretical reasoning draws on the literature of inter-organizational "inheritance". By working at a prominent company (the "parent") in the past, an entrepreneur inherit human and

[2] http://10years.firstround.com/. Accessed September 2, 2015.

social capital that may be useful for her new venture (e.g. Agarwal et al. (2004)). Therefore, coming from a prominent former employer signals better quality of the venture, and thus will have less difficulty getting funded and also are more likely to attract top-tier investors. In addition, the human and social capital are more relevant for the new venture if it shares a similar business model, similar practices or similar needs for resources with the parents. Therefore, we also expect working for prominent companies to be more useful for entrepreneurs if they choose to start a business that shares these similarities with the parents.

We answer the research question empirically using data from CrunchBase, an online directory of companies, individuals and investors in the technology startup community. As our analyses first show, compared with ventures started by employees from less prominent companies, spawns are more likely to be acquired or become public, and are more likely to secure series A financing. They are also more likely to attract top-tier investors. However, those differences exist for only spawns who operate in a line of business similar to their parents.

To exclude the confounding selection issue outlined above, we draw on an instrumental variable approach. We instrument for the status of spawn using the proportion of new hires employed by the prominent companies in the industry-year a founder started working. This instrumental variable seems plausible, because it strongly correlates with the endogenous variable and an individual's entrerpeneurial ability is unlikely to correlate with the jobs created by the prominent companies. The regression results are robust to the use of the instrumental variable, lending confidence to causally inferring the impact of working for a prominent company.

Secondly, we also find that compared with their less prominent counterparts, prominent employers mainly prepare entrepreneurs for managing their ventures after entry rather than timing the market before entry. It seems that the inherited human and social capital from prominent companies is more useful for managing the new venture after entry than timing the market before entry. One possible explanation for this is that the knowledge of business management is more "teachable" from former employers than the knowledge of market timing (Kogut and Zander, 1993). Even for top-notch industry experts, it is often difficult to foresee where and when the "next big thing" will emerge, as it depends on a complicated set of factors such as consumer demand, technology and macroeconomic conditions. As an example, Microsoft, Apple and RealPlayer all had video streaming products by the late 1990s, but they never took off because of slow internet speed and lack of a standard format. With the mass adoption of broadband connection and Adobe Flash as the standard streaming format, Youtube became an immense success soon after its launch in early 2005.[3] Even if some people at the former employers have the exceptional ability of market timing, it is difficult for them to teach others because this ability is hard to codify (Kogut and Zander, 1993). Therefore, it is possible that prominent employers have little edge in teaching market timing than the less prominent employers.

On the other hand, prominent companies often pride themselves in the more advanced management, such as incentive schemes to motivate employees and human resource techniques for creating a collaborative culture. Many of these management practices can be codified. Working at a prominent company also provides access to potential co-workers or investors for the entrepreneurs' new venture. Therefore, prominent employers are likely to make a greater impact on the management of the new venture than on its market timing.

4.2 Literature on Spawns' Advantage

We focus on the performance and early-stage financing of spawns. The literature has documented spawns' advantages in both. And the mechanism has generally been illustrated as one of "inheritance": entrepreneurs that come from working for a prominent company inherit human and social capital that may be valuable for the new ventures. From prominent employers, would-be entrepreneurs learn human capital that is useful for managing a new venture. Prominent companies tend to build on time-tested business practices that differentiate themselves from others. Many of those practices would help to bring a new venture on track. For example, employees may absorb commercial, technological, regulatory know-hows or certain routines when they leave to start

[3] http://blog.treepodia.com/2012/02/a-short-history-of-online-video-part-1-before-youtube/. Accessed September 2, 2015.

their own ventures (Agarwal et al., 2004; Phillips, 2002). Those know-hows become part of the entrepreneurs' human capital, and contributes to the new ventures' success (Colombo and Grilli, 2005; Dick et al., 2013). From prominent employers, would-be entrepreneurs also accumulate social capital that helps with the business operation of the new ventures. For example, prominent employers boast higher-caliber talent, making it easier for would-be entrepreneurs to find start-up partners (Campbell et al., 2012; Agarwal et al., 2013). Leaving as a team to start a new venture is particularly relevant when the knowledge is complicated, or is embedded in a group rather than in individuals (Ganco, 2013; Kogut and Zander, 1992).

In essence, the inheritance of human and social capital represents knowledge transfer from the parents to the new ventures. The knowledge transfer contributes to better performance for the new ventures. Indeed, prior studies have documented longer survival of startups where their founders used to work at incumbent firms (Eriksson and Moritz Kuhn, 2006). In the medical device industry, spawns have been found to be more proficient in dealing with regulations (Chatterji, 2009).

Spawns' advantages are reflected in the early-stage financing as well. External financing is critical to the growth and success of nascent businesses. So are the value-adding services that often come along with the financial capital. In particular, with their certification and provision of guidance and resources, prominent investors are much sought after by new ventures, to the extent that entrepreneurs would offer equity at a discount in order to compete for reputable buyers (Hsu, 2004; Hellmann and Puri, 2002). The entrepreneurs' consideration can be summarized as "It is far more important whose money you get than how much you get or how much you pay for it."(Bygrave and Timmons, 1992). Despite its importance, securing external financing is a critical challenge confronting new ventures, with only a small portion getting funded and even fewer funded by prominent or reputable investors. A widely documented reason behind this challenge is information asymmetry. Investors often find it difficult to assess the quality of nascent businesses, as the latter typically lacks sufficient operating history or tangible assets. The information asymmetry causes market failure, resulting in ventures being under-financed (Stiglitz and Weiss, 1981). In addition, the scarcity of prominent investors renders themselves difficult to access for many entrepreneurs. Given the inherited human and social capital, spawns are a more favorable target for investors. They are also more likely to match with top-tier investors.

4.3 Empirical Analyses

4.3.1 Context

We test the hypotheses using data collected from CrunchBase in 2015. CrunchBase is an online directory of companies, individuals and investors in the technology sector. Its spectrum of coverage ranges from the "hard-tech" industries such as hardware and semiconductor to the "soft-tech" ones such as mobile applications. The database updates its content in two ways. First, it automatically gathers information from a list of popular websites that reports the dynamics of the technology sector. Second, as a free and open platform, it allows registered users to edit its content. Before becoming public, all edits are subject to approval by the administrators. Since its launch, CrunchBase has gained increasing popularity in the technology startup community, and has become a major source of information for both entrepreneurs and investors.

The more commonly-used startup databases, such as Thompson One (formerly known as "VentureXpert") and VentureSource, typically cover only companies that are backed by venture capital (VC) firms. In contrast, CrunchBase has the distinct advantage of covering both companies that are externally funded and those that are not. As externally funded startups account for only a small portion of the population, and are probably sampled from the right tail of the quality distribution, using CrunchBase provides a more representatitive picture of the technology startups. In addition, specific to the purpose of this study, the commonly-used databases lack variation on the extensive margin of external financing.

The coverage of CrunchBase is comparable to that of the other data sources. For instance, it covers about the same number of investment deals in the corresponding sector as recorded by the National Venture Capital Association (Block and Sandner, 2009).

In this study, we restrict the sample to U.S. technology startups founded between 2005 and

2011. The rationale is twofold. First, including startups that are too young may aggravate the censoring issue and possibly lead to underestimation of the spawns' advantage, so we leave out startups less than four years old. Second, CrunchBase was established in 2007. Startups founded much earlier than that may be selectively entered into its database, thus possibly creating the "survivorship bias." The choice of the year 2005 accounts for the time it takes new startups to create an online presence.

4.3.2 Key Measures

A key aspect in testing the hypotheses is to operationalize the "prominence" of the companies and of the investors. For the companies, we measure their prominence by the total number of (past or present) employees on CrunchBase. This prominence measure captures a company's representation and influence in the technology startup community. Out of the total 300,000 organizations featured on CrunchBase, we define "prominent employers" to be the 100 with the most employees registered on the website. Table 4.1 presents the top and bottom 10 of the prominent employers. The list features mostly household names in the technology startup community, lending credence to our measure. Following the binary approach in the literature, we define "spawns" as startups with at least one founder being a former employee at a prominent company (Chatterji, 2009). And for a spawn, we call the corresponding prominent company its "parent".

For the investors (both institutions and individuals), we define "prominent investors" in a year to be the top 10 percent of all investors by the cumulative number of exits up to (including) that year. An exit refers to the event of a funded startup being acquired or going public. This measure is based on an investor's performance, which reflects its status in the technology startup community.

Consistent with the literature, we operationalize the success of a startup as being acquired or becoming public (e.g. Gompers et al. (2010)). As for early stage financing, we focus on series A round. This is the first major round of venture financing for startups, with amount typically exceeding one million U.S. dollars.[4]

[4]Early-stage financing also includes angel or seed rounds. However, in those rounds, deals are generally made

Table 4.1: List of Prominent Companies: Top 10 and Bottom 10

Top 10		Bottom 10	
Company Name	Representation	Company Name	Representation
Microsoft	1785	Netscape	145
Google	1562	NBC Universal	144
IBM	1222	Investcorp Gulf Investments	144
Yahoo!	1170	Andersen Consulting	143
McKinsey	966	Amgen	142
Oracle	912	DoubleClick	142
Hewlett-Packard	870	American Capital	140
Cisco	758	Cap Gemini	140
Intel	717	Silicon Valley Bank	140
Accenture	713	Samsung Electronics	140

At the time of our collection, the CrunchBase database no longer applied industry categories to the companies. We derive the industry classification from a company's textual description. For most companies, a piece of text (typically in a couple of paragraphs) describes the nature of its business. On these texts, we run a topic modeling technique termed Latent Dirichlet Allocation (LDA) (Blei et al., 2003). All the coampanies on CrunchBase are then each classified into one of 20 industries.[5]

To measure business similarity between two companies, we compute cosine similarity using the weights of the industries. The weights are produced by LDA using the companies' description (Shi et al., 2014).[6] Thus, the dyadic business similarity score is bounded between 0 and 1, with larger values indicating greater similarity in terms of the nature of the business. In this analysis, we categorize the spawns into "high-similarity" ones, *i.e.* those that are more similar to their founders' former employers and "low-similarity" ones, *i.e.*, those that are less so. The cut-off value is the median of the similarity score, which happens to be 0.

informally and thus subject to under-reporting.

[5]See the Appendix for the list of the industries and an introduction to LDA.

[6]Please refer to the appendix for the technical details.

Table 4.2: Sample Description

	Spawns				Non-Spawns			
	High Similarity		Low Similarity		Non-Prom. Employers		No Reported Employers	
	%	N	%	N	%	N	%	N
Founded in 2005	5.8	466	5.1	489	5.8	2024	6.5	9204
Founded in 2006	8.6	466	8.2	489	8.2	2024	8.6	9204
Founded in 2007	14.0	466	11.5	489	10.4	2024	12.0	9204
Founded in 2008	15.2	466	13.1	489	11.0	2024	13.2	9204
Founded in 2009	13.3	466	16.2	489	15.1	2024	16.5	9204
Founded in 2010	19.3	466	24.8	489	21.7	2024	19.3	9204
Founded in 2011	23.8	466	21.3	489	27.8	2024	23.9	9204
Had Prior Startup Experience	49.1	466	45.2	489	41.0	2024	11.4	9204
Was Acquired or Went Public	25.3	466	18.6	489	15.7	2024	9.7	9204
Secured Series A Financing	46.2	466	32.9	489	29.9	2024	16.8	9204
Secured A Rnd by Prom. Investors	27.9	466	16.4	489	13.8	2024	5.9	9204
Percent of New Hires by Prominent Employers in the Industry-Year the Founder Started Working	13.3%, N=1020				5.0%, N=11205			

4.3.3 Regression Analyses

To test the aforementioned hypotheses, our main strategy is to compare four groups of new ventures: (1) high-similarity spawns, (2) low-similarity spawns, (3) ventures founded by former employees from non-prominent employers and (4) ventures whose founders do not report former employers on CrunchBase. Founders in the last group either did not work before, or their employers do not have an account on CrunchBase. In the latter case, they are likely to have worked for a company that is not related to the technology startup community.

Table 4.2 presents an overview of the sample. Spawns only account for a fraction of the sample, and are pretty evenly distributed between the high- and low-similarity groups. The four groups are similarly distributed by founding year. Spawns consist of a higher proportion of serial founders. From the descriptive statistics, spawns are more likely to get acquired or become public, and are more likely to secure series A financing. In addition, prominent investors also seem to favor spawns. It is noteworthy that compared with ventures founded by employees from non-prominent companies, spawns seem to have an advantage only their similarity with parents is high.

We use the Cox proportional-hazards model to test whether spawns have advantages in performance and early-stage funding. The model is:

$$\lambda_i(t) = \lambda_i^0(t)\exp(\alpha + HighSimSpawn_i \cdot \beta_1 + LowSimSpawn_i \cdot \beta_2 + NonPromEmployer_i \cdot \beta_3 + \mathbf{X_i} \cdot \gamma)$$

where $\lambda_i^0(t)$ denotes the baseline hazards of receiving financing for startup i at time t. $HighSimSpawn_i$ and $LowSimSpawn_i$ are binary indicators for respectively high- and low-similary spawns (Groups (1) and (2)). $NonPromEmployer_i$ is a binary indicator for ventures started by employees from non-prominent companies (Group (3)). $\mathbf{X_i}$ is a set of control variables including whether any founder had prior entrepreneurial experience and fixed effects for industry, state and founding year. We are primarily interested in the coefficients β_1, β_2 and β_3, and their pairwise comparison. The choice of the Cox model has the advantage of being robust to censoring. Alternatively, we also specify an ordinary least square (OLS) model. The results are qualitatively similar.

As mentioned above, simply comparing the four groups does not inform the causal effects of working for prominent companies, because the founders may differ by group in their inherent abilities (e.g. cleverness). To test the causal effects, we use an instrumental variable (IV) approach. The IV we use is the percent of new hires by the prominent companies in the industry-year a founder started working. In the computation, we exclude the focal founder to avoid the reflection issue. If a startup has multiple founders, we take the highest value as the IV for the startup. This IV draws on the industry-year variation. Whereas company- or person-specific IVs may capture more variation, IVs drawing on industry or yearly variation are not uncommon in the entrepreneurship literature. For example, Nanda and Rhodes-Kropf (2013) and Gompers and Lerner (2000) use the amount of buyout fund raising in a one-year period to instrument for the venture capital investments. Relatedly, Samila and Sorenson (2011) instrument venture capital investments with the average returns to limited partners in a two-year period.

The choice of the IV is predicated on two conditions. First, the IV should be correlated with the endogenous variable, otherwise there may be the "weak IV" problem. In the sample, the correlation between the IV and the status of being a spawn is around 0.43. The first-stage F-statistics is close to 20 in the regressions, passing the general rule-of-thumb value of 10. Intuitively, the IV correlates with the spawn dummy because the the higher the labor demand by the prominent companies when a founder started working, the more likely the founder worked for a prominent company, and the more likely the new venture is a spawn. Second, the IV should satisfy the "exclusion restriction" condition, that is, the IV cannot be associated with the founders' entreprenerial ability. This condition is likely to hold as well, because the percentage of new hires accounted by the prominent companies in any particular year is mainly driven by factors at the levels of the corporations, the industry and the macroeconomy, and is unlikely associated with the abilities of a new entrant to the labor market.

As we have only one IV, we compare the spawns (Groups (1) and (2)) with the other ventures (Groups (3) and (4)). A two-stage IV model is specified below:

$$
\begin{aligned}
Spawn_i &= \eta + \theta \cdot PromJob_i + \mathbf{X_i}^\top \cdot \psi + \mu_i \\
y_i &= \alpha + \gamma \cdot \widehat{Spawn}_i + \mathbf{X_i}^\top \cdot \beta + \varepsilon_i
\end{aligned}
$$

where $PromJob_i$ is the IV. We are primarily interested in the coefficient γ, which represents the local average treatment effects of working for prominent companies. As shown in Table 4.2, on average the spawns have a significantly higher IV value than the other ventures. The make the spawns and non-spawns more comparable, we also run both stages using weights constructed following Rawley and Simcoe (2010). We first estimate a probit model that regresses the binary indicator of being a spawn on the control variables. Then we drop observations outside the common support of the predicted probability. For the spawns, the weights are constructed as the inverse of the predicted probability; for the non-spawns, the weights are the inverse of one minus the predicted probability.

In addition, to test whether spawns are more likely to be funded by prominent investors, we specify an ordered logit model. The dependent variable is a ordinal variable with three values: 0 =

Table 4.3: Spawns' Advantages: Regression Coefficients

	Dummy: Acq/IPO		Dummy: Series A		Categories by Investor Prominence
	Cox	IV-OLS	Cox	IV-OLS	Ordered Logit
	(1)	(2)	(3)	(4)	(5)
Spawn		0.051*		0.146***	
		(0.028)		(0.038)	
(1) Spawn-Hi	0.719***		0.688***		1.245**
	(0.075)		(0.042)		(0.075)
(2) Spawn-Lo	0.444***		0.411***		0.738***
	(0.168)		(0.048)		(0.080)
(3) Non-Prom Employer	0.330***		0.411***		0.619***
	(0.094)		(0.045)		(0.044)
Prior Startup Exp	0.293***	0.051***	0.264***	0.062***	0.343***
	(0.036)	(0.010)	(0.029)	(0.012)	(0.047)
State FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Founding Yr FE	Yes	Yes	Yes	Yes	Yes
p-value: (1)=(2)	0.077		0.000		0.000
p-value: (1)=(3)	0.000		0.000		0.000
p-value: (2)=(3)	0.464		0.994		0.072
First-Stage F-Stat		19.39		19.39	
N	12113	11482	12027	11482	12121

Notes:

i. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by state.

ii. Columns (2) and (4) report second-stage coefficients. Both stages are weighted.

not receiving series A; 1 = funded by non-prominent investors in series A; 2 = at least one investor is prominent in series A. The right-hand-side variables are the binary indicators for Groups (1)-(3) and the control variables specified above.

The regression results, as summarized in Table 4.3, confirm the patterns in the descriptive statistics. The spawns have higher chances of being acquired or becoming public, and are also more likely to secure series A financing. They are also more likely to be funded by top-tier investors at an early stage. The IV regressions lend confidence to causal inference—the prominent employers do prepare entrepreneurs for their success. However, compared with ventures spinned out from non-prominent companies, a spawn seems to have an advantage only if it operates in a line of business similar to its parents.

Next, we turn to the question of what entrepreneurial abilities prominent companies help their employees develop. Following Gompers et al. (2010), we broadly classify entrepreneurial abilities into two categories: market timing and management. Market timing ability refers to the ability to enter the right industry at the right time. This ability can be important as the market conditions change from one year to another. For instance, in our sample, 5.6 percent of "social network" startups founded in 2008 was acquired or went public within five years of founding, but the rate is only 1.8 percent for the "social network" cohort founded in 2007. On the other hand, management abiltiy refers to the skills for running the business after entry. It may encompass a wide range of issues such as project management, human resources and marketing etc.

We first run an OLS regression to distinguish these two abilities. The dependent variable is a binary indicator if the venture was acquired or became public within five years of founding.[7] The right-hand side includes year fixed effects, industry fixed effects and the "cohort success rate"—the percentage of the year-industry cohort being acquired or going public within five years of founding. From this regression, the predicted value is referred to as the "market timing score", and the residual is the "management score" of a startup. Then, respectively using these two scores as dependent variable, we run OLS regressions to test whether spawns also have greater entrepreneurial abilities.

The results are tabulated in Table 4.4. Spawns' market timing ability differs only slightly from the others', but they have significantly higher management scores. And echoing the findings about performance and funding, only spawns with similar business to their parents have better management ability than spinouts from non-prominent employers.

4.4 Conclusion

Working experience at a prominent company does benefit entrepreneurs. Compared with less prominent companies, the prominent ones helps build up employees' ability to manage a venture,

[7] We also examine a seven-year window. These two measures have a correlation coefficient of 0.79.

Table 4.4: Entrepreneurial Abilities: Market Timing vs. Management

	Dummy: Acq/IPO	Market Timing Score	Management Score
	OLS	OLS	OLS
Cohort Success Rate	1.000***		
	(0.068)		
Spawn-Hi		0.002	0.229***
		(0.002)	(0.026)
Spawn-Lo		0.007***	0.115***
		(0.002)	(0.013)
Non-Prom Employer		0.002*	0.096***
		(0.001)	(0.009)
Prior Startup Exp		0.002**	0.064***
		(0.001)	(0.008)
State FE	No	Yes	Yes
Founding Yr FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
p-value: (1)=(2)		0.069	0.000
p-value: (1)=(3)		0.956	0.004
p-value: (2)=(3)		0.087	0.193
N	12121	12121	12121

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard Errors are clustered by state.

but does not seem to offer much help for identifying market opportunities. In addition, spawns have better performance and greater chances of early stage funding, but only if they operate in a business similar to their parents. Further, the results show that entrepreneurs without any work experience or whose former employers are not in a relevant industry underperform others.

The findings have two practical implications. First, they point to business similarity as an important boundary condition for spawns' advantage. Drifting too far from parents' lines of business makes it difficult for spawns to translate the inherited human or social capital into success. Second, for individuals considering becoming an entrepreneur, rushing in without any experience in the industry may not be advisable. One way to prepare successful entrepreneurs is through working for a prominent company in the industry.

Appendix for Chapter 4: Industry Classification and Business Similarity

In this paper, we derive the industry classification and compute dyadic business similarity using the startups' description at CrunchBase. The description is typically a piece of text, usually in a couple of paragraphs, that summarizes the business of the company. As an illustrating example, the following is the description for the company Twitter:

```
   Twitter is a global social networking platform that allows its users
to send and read 140-character messages known as ``tweets''.  It enables
registered users to read and post their tweets through the web, short
message service (SMS), and mobile applications.
   As a global real-time communications platform, Twitter has more than
400 million monthly visitors and 255 million monthly active users around
the world.  Twitter's active group of registered members includes World
leaders, major athletes, star performers, news organizations, and entertainment
outlets.  It is currently available in more 35 languages.
   Twitter was launched in 2006 by Jack Dorsey, Evan Williams, Biz Stone,
and Noah Glass.  It is headquartered in San Francisco, C.A. with local
offices in Atlanta, Austin, Boston, Boulder, Chicago, Detroit, Los Angeles,
New York, Seattle, Sunnyvale, and Washington.  Twitter's international
offices are located in Amsterdam, Berlin, Dublin, London, Madrid, Paris,
Rio de Janeiro, São Paulo, Singapore, Sydney, Seoul, Tokyo, Toronto,
and Vancouver.
```

For an individual company, we first use Latent Dirichlet Allocation (LDA), a topic modeling technique, to generate a series of weights over a specified number of industries. The weights are then used to determine the primary industry for the company, as well as to produce a cosine similarity measure for a pair of companies. LDA falls into the category of unsupervised machine learning, and has been used for classification in the computer science literature(Fang et al., 2013). Recently, LDA has also started to be used in the economics literature (Hansen et al., 2014). It works as follows:

A description d is a set of words $\{w_d^j | j = 1, 2, ..., L_d\}$, where L_d is the number of words in d. Let D be the number of descriptions in the sample. Let W be the set of all the words in all the descriptions. We specify K industries. Industry $k \in \{1, 2, ..., K\}$ is characterized by p_k, a probabilistic distribution over W. We denote p_k^w as the probability of the word w appearing in the description if the industry is k. The likelihood of the description d belonging to a company in industry k is q_d^k. Then, the likelihood of d being observed is a product of the likelihood of its individual words being observed:

$$\prod_{j=1}^{L_d}(\sum_{k=1}^{K} q_d^k \cdot p_k^{w_d^j})$$

For computational efficiency, LDA estimates p and q using Bayesian estimation. Assuming Dirichlet priors for p and q with parameters θ and δ respectively. Then, the joint likelihood function is:

$$\prod_{k=1}^{K} Pr(p_k|\theta) \cdot \prod_{d=1}^{D} Pr(q_d|\delta) \cdot \prod_{j=1}^{L_d}(\sum_{k=1}^{K} q_d^k \cdot p_k^{w_d^j})$$

From that we may derive the posterior distribution using Markov Chain Monte Carlo. The estimates produce a weight for each word in each industry. For a given company, from its description and the estimated weights on words, we can generate a weight for each industry. The industry with the highest weight is designated as the company's primary industry.

In this paper, we first let $K = 25$. Then we browse the keywords with the greatest weight in each industry, and eliminate five industries where the keywords are unlikely to inform a line of business.[8] To (roughly) profile each of remaining 20 industries, Table 4.5 lists the five words with the greatest weights. It also shows how the industries are distributed in the sample. On CrunchBase, the most popular industries seem to be related to social network, marketing and data analytics.

From the K industry weights for each company, we can compute the dyadic business similarity as the cosine similarity between company i and j:

[8] As an example, one industry we eliminated contains a string of the following keywords: "founded", "based", "states", "united" and "san".

Table 4.5: Top 5 Words for Each Industry from Latent Dirichlet Allocation

Industry No.	Top 5 Words	Authors' Interpretation	% Sample
1	data, information, analytics, solution, time	data analytics	10.9
2	payment, money, customers, credit, offers	consumer finance	6.1
3	video, music, content, media, sports	entertainment/sports	5.6
4	job, insurance, law, legal, jobs	legal/human resources	1.9
5	fashion, accessories, store, quality, shopping	fashion/retails	3.0
6	design, marketing, website, search, seo	web design	4.0
7	systems, wireless, devices, offers, communications	communication system	3.8
8	news, information, site, content, media	news	5.4
9	apps, games, app, applications, game	mobile apps	3.4
10	capital, investment, companies, venture, firm	investment	1.5
11	health, care, healthcare, medical, patients	healthcare	3.4
12	energy, power, systems, solar, industries	energy	4.1
13	students, education, learning, training, school	education	3.0
14	medical, develops, research, treatment, based	medical research	7.1
15	users, share, people, allows, friends	social network	12.8
16	repair, garage, door, home, car	home improvement	0.4
17	food, restaurants, restaurant, wine, coffee	catering	0.9
18	marketing, media, advertising, digital, content	marketing	13.1
19	travel, real, estate, property, hotel	travel	2.5
20	data, security, cloud, enterprise, applications	security/cloud	7.3

$$BusinessSimilarity_{i,j} = \frac{\sum_{k=1}^{K} W_{i,k} W_{j,k}}{\sqrt{\sum_{k=1}^{K} W_{i,k}^2} \cdot \sqrt{\sum_{k=1}^{K} W_{j,k}^2}}$$

where $W_{i,k}$ is the company i's weight in industry k. The business similarity measure is bounded between 0 and 1, with larger values indicating greater similarity between two companies' business.

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