PRELIMINARY DRAFT

Taking the Leap: The Determinants of Entrepreneurs Hiring their First Employee

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Abstract

Job creation is one of the most important aspects of entrepreneurship, but we know relatively little about the hiring patterns and decisions of startups. Longitudinal data from the Integrated Longitudinal Business Database (iLBD), Kauffman Firm Survey (KFS), and the Growing America through Entrepreneurship (GATE) experiment are used to provide some of the first evidence in the literature on the determinants of taking the leap from a non-employer to employer firm among startups. Several interesting patterns emerge regarding the dynamics of non-employer startups hiring their first employee. Hiring rates among the universe of non-employer startups are very low, but increase when the population of non-employers is focused on more growth-oriented businesses such as incorporated and EIN businesses. If non-employer startups hire, the bulk of hiring occurs in the first few years of existence. After this point in time relatively few non-employer startups hire an employee. Focusing on more growth- and employment-oriented startups in the KFS, we find that Asian-owned and Hispanic-owned startups have higher rates of hiring their first employee than white-owned startups. Female-owned startups are roughly 10 percentage points less likely to hire their first employee by the first, second and seventh years after startup. The education level of the owner, however, is not found to be associated with the probability of hiring an employee. Among business characteristics, we find evidence that business assets and intellectual property are associated with hiring the first employee. Using data from the largest random experiment providing entrepreneurship training in the United States ever conducted, we do not find evidence that entrepreneurship training increases the likelihood that non-employers hire their first employee.

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1. Introduction

Many policymakers and organizations have called upon entrepreneurs to create new jobs. For example, President Obama has repeatedly emphasized the importance of startups and small businesses in creating jobs, and has signed laws such as the Small Business Jobs Act of 2010 and the Jumpstart Our Business Startups (JOBS) Act of 2012, which aim to create jobs through promoting small businesses. The focus on the job creation potential of entrepreneurs also exists in Europe and other countries around the world (OECD 2014).

Several previous studies examine the impact of small businesses on employment. Starting with the seminal study by Birch (1979) showing that small businesses were the principal driver of job creation in the U.S. economy and recent refinements of this argument to focus on young and high-impact firms, there has been considerable interest in what types of firms generate jobs. Recent evidence indicates that young and high-impact businesses (defined as having high rates of growth in sales and employment) account for essentially all net jobs in the economy (Haltiwanger, Jarmin and Miranda 2013 and Tracy 2011). Often overlooked is that self-employed business owners also create jobs for themselves, representing more than 10 percent of total employment in the United States and that many employer businesses start as non-employers (Davis et al 2007).

But, hiring employees represents one of the major thresholds that entrepreneurs encounter when growing their businesses. The step from non-employer to employer entails additional registration and legal requirements; health insurance, workers compensation and unemployment insurance issues, and the ongoing burden of making payroll. Navigating through filing for an employer identification number, federal wage and tax statement (Form W-2), employee eligibility verification (Form I-9), state new hire reporting program, workers' compensation insurance program, unemployment insurance tax registration program, and disability insurance in some states may be especially daunting to small business owners considering hiring their first employee. But perhaps the most important consideration for the owner is whether current and future revenues are large enough to cover the extra expenses of having employees. Surprisingly, given its importance there is very little research on the topic.

This paper examines four main questions related to the decision by entrepreneurs to hire their first employee that have not been examined in detail in the previous literature. First, what are the dynamic patterns of hiring employees among startups in their first few years of existence? Second, what are the demographic and human capital characteristics of entrepreneurs that are associated with making the decision to hire their first employee in the first several years of operation? Are female, minority and immigrant owners less likely to cross the employer threshold? Are more educated entrepreneurs more likely to hire their first employee in the first years of existence? Third, can an alternative form of human capital, entrepreneurship training, help overcome some of the barriers to hiring employees? Entrepreneurship training often specifically teaches self-employed business owners strategies for hiring and managing employees, and provides training on registering for EINs, tax and insurance compliance, and legal issues, but does it increase the likelihood of hiring the first employee? Finally, what dynamic business conditions are associated with hiring the first employee? Is there a sales or business asset milestone that firms often reach before hiring their first employee? Do non-employer firms typically have intellectual property, such as patents, copyrights and trademarks, before hiring their first employee?

In addition to the previous research on the impact of small businesses on employment in the United States, a few recent studies examine the relationship and growth patterns between non-employer to employer businesses. Acs, Headd and Agwara (2009), for example, find that non-employers have a startup rate of 35 percent, which is nearly three times the startup rate of employer firms. Using matched data from the Census Bureau, Davis et al. (2007) find that a significant number of new employer firms start as non-employer firms. The link between non-employer and employer status and how it is related to reaching business milestones and owner characteristics, however, has not been previously examined in detail.

Another strand of research indicates variation in employment rates and average number of employees by demographic and human capital characteristics of the business owner. Parker (2009) reviews the literature and reports evidence of positive effects from education, age, experience, male, parental self-employment, wealth and industry.[1] Three factors that especially stand out are minority, female ownership and education. In the United States, for example, Substantial disparities exist between minority vs. non-minority owned firms and female vs. male owned firms, for example: 13.3 percent of minority-owned firms hire employees compared with 21.6 percent of non-minority owned firms, and 11.7 percent of female-owned business hire employees compared with 23.2 percent of male-owned businesses (U.S. Census Bureau 2013).[2] The education level of the business owner is also associated with hiring employees, with 32 percent of owners with a university degree hiring employees compared with 28 percent of owners with a high school degree or lower level of education hiring employees.[3] These findings, however, are for all existing businesses and do not capture the relationship between owner characteristic and the employment decision when that decision is made. Previous research also

[1] Also, see Burke et al. (2000, 2002), van Praag and Cramer (2001), Cowling et al. (2004), Henley (2005), and Fairlie and Robb (2007).
[2] See Fairlie and Robb (2008) for a review of the literature on racial and ethnic patterns in business employment.
[3] See van der Sluis, van Praag and Vijverberg (2005) for evidence on the relationship between education and business outcomes.

does not focus on startups, and hiring patterns may differ substantially for all new businesses than for the subsample of businesses that survive up to the survey year.

In this paper, we use data from three sources: 1) the U.S. Census Bureau's Integrated Longitudinal Business Database (iLBD) which provides panel data on the universe of non-employers matched to employers over time, 2) the Kauffman Firm Survey (KFS) which provides panel data on detailed owner and business characteristics and follows growth-oriented startups over the first several years of existence, and 3) the Growing America through Entrepreneurship (GATE) experiment which is the largest random experiment on the effects of entrepreneurship training ever conducted. Using these data this paper provides one of the first detailed longitudinal studies of the owner, business, and training determinants of non-employers hiring their first employee. The novel results from the iLBD provide the first evidence in the literature on hiring patterns among the universe of non-employer startups.[4]

The limited previous research on the topic appears to be due to data limitations. Very few datasets provide information on the time at which a business hires its first employee, owner and business characteristics, and longitudinal information on business conditions or milestones. Additionally, no previous datasets have information allowing for a credible method of identifying whether entrepreneurship training helps business owners hire their first employee.

2. Data

Three datasets, the Integrated Longitudinal Business Database (iLBD), the Kauffman Firm Survey (KFS), and the Growing America through Entrepreneurship (GATE) Project, are

[4] These results from the new and revised iLBD complement earlier results reported in Davis et al. (2007). Two major differences in the current study is that we focus specifically on the population of startups and that we include all industries.

used in this study. All three datasets provide difficult-to-find information on when a non-employer business hires its first employee. Each dataset has strengths to contribute to the overall analysis of patterns and determinants of non-employer businesses hiring their first employee. The confidential and restricted-access iLBD provides administrative information on the universe of non-employer firms. These data provide a comprehensive view of patterns of non-employer startups hiring employees over time. The KFS and GATE also provide detailed information on the characteristics of the owner and business prior to when the business hires its first employee. All three panels provide information at the point in time of hiring instead of less reliable retrospective information. All three datasets provide longitudinal data that follows businesses over several years.

To our knowledge, the iLBD and KFS are the only two nationally representative datasets that provide information on non-employer startups making the transition to employer firms. Additionally, the only dataset providing information on non-employers hiring employees at the point of time of hiring and providing an experiment in which entrepreneurship training is randomly allocated is the GATE data. Although GATE is not nationally representative it does cover urban and rural populations across 14 different organizations in three different states.

Integrated Longitudinal Business Database (iLBD)

We use the U.S. Bureau of the Census confidential and restricted-access integrated Longitudinal Business Database (ILBD). The iLBD covers the universe of non-employer and employer business units in the nonfarm private sector of the U.S. economy. It is constructed by linking employer and non-employer businesses units by a variety of identifiers including the EIN, the SSN, and the name and address of the owner or business (for details on the construction of this dataset, see Davis et al, 2007). We focus our analysis on non-employer businesses that transition to employer status. We include the full population of non-employer business and impose no restrictions in terms of industry, revenue, age of the business owner, or number of hours spent in the business.[5] We define a non-employer startup as a business with no activity in the four years prior be it as a non-employer or as an employer. We start from the population of non-employer startups in 1997. We follow their transitions out of the non-employer population either as a permanent exit or as a transition into employer status. A permanent exit requires that the EIN, SSN, or business name do not appear again in the iLBD either as an employer or as a non-employer. To this end we examine iLBD data through 2011. A transition to employment status takes place when we are able to identify a non-employer business unit in the employer universe. We track transitions up to 7 years after startup.

The iLBD cover the universe of non-employer startups. Every business that is registered is included. The iLBD contains information on the legal form; sole proprietor, partnership or corporation, the type of tax identifier; EIN or SSN, revenue size, and industry. It does not contain any information on the owner. As discussed below the iLBD contains a large number of business activities that have no intention of hiring employees and represent consulting or contracting activities. But, these data provide a useful view of the universe of non-employer business units, and we are able to identify more growth-oriented businesses by conditioning on a few of the administrative variables in the iLBD.

The Kauffman Firm Survey

[5] We also do not limit ourselves to migrant transitions as defined by Davis el al (2007) and examine instead all transitions to employer status.

The KFS, conducted by the Kauffman Foundation, is a panel study of 4,928 businesses founded in 2004. See Robb et al. (2010) for a detailed description of the KFS. The business startups were surveyed in 2004 (baseline) and annually after that date. The most recent year of available data is the seventh follow-up survey conducted in 2011. These data were released in spring 2013 and are the final wave planned for the KFS. The sampling frame for the KFS is the Dun & Bradstreet database started in 2004. The definition of a startup used in the KFS is whether at least one of several business indicators were present for the first time in 2004. The indicators include payment of unemployment insurance taxes, payment of FICA taxes, presence of a legal status for the business, presence of an employer identification number (EIN), and use of schedule C to report business income. Thus, the KFS definition of a business start is somewhat unique and include a disproportionate number of more "advanced," growth-oriented or employment-oriented non-employer startups.

The panel dataset provided in the KFS provides an unprecedented source of data on business startups in their early years of operation.[6] Detailed information on each firm includes employment, industry, physical location, sales, profits, and business assets at start-up and over time.[7] The KFS also includes detailed information on intellectual property, such as patents, copyrights, and trademarks. The detailed information on employment and other business activity provided annually in the KFS allows for an examination of the dynamic relationship between

[6] For more information about the KFS survey design and methodology, please see Ballou et al (2008).
[7] The KFS also includes detailed financing information. These variables, however, are not included in the analysis because of endogeneity concerns. For example, if a firm needs to hire employees prior to production then the only method of doing this is to obtain financing. In this case, however, the financing did not cause the business to hire the employee, but instead the need to hire employees caused the business to find financing. Similar concerns have been noted in the literature examining liquidity constraints for business creation. See Parker (2009), Kerr and Nanda (2011), and Fairlie and Krashinsky (2012) for recent discussions of the literature.

these factors and employment among new businesses. Most importantly, it allows for an analysis of business and owner characteristics at the time young businesses hire their first employee.

The KFS also provides detailed information on owner characteristics such as age, gender, race, ethnicity, education, and prior work experience.[8] This information is useful for identifying the characteristics of owners that hire employees within the first several years of operation. Panel data allow for measurement of these characteristics year by year, and thus immediately prior to when non-employer startups make the decision to hire their first employee.

Robb et al. (2010) provide a detailed comparison of the KFS to several commonly used business-level datasets. These comparisons, however, include the full sample of businesses in the KFS. To examine the representativeness of the KFS sample of non-employer startups used in this study, estimates are compared to estimates from the 2004 iLBD and the 2007 Survey of Business Owners microdata for a roughly similar population (defined as all non-employer businesses started in the previous year). Appendix Table 1 reports estimates of the industry distribution from all three datasets. For most industries, the KFS, iLBD and SBO are roughly similar in representation. The main exceptions are that the KFS non-employer startup sample is overrepresented in manufacturing and wholesale trade, and underrepresented in health and educational services compared with the new non-employer sample in the SBO.

GATE Experiment

Growing America through Entrepreneurship (Project GATE) is an evaluation designed and implemented by the U.S. Department of Labor and U.S. Small Business Administration. The

[8] Owner characteristics are identified for the primary owner of the business. The primary owner of multi-owner businesses is identified by the largest equity share in 2004 with ties being allocated by comparing hours worked and other variables (see Robb et al. 2010). Thanks to Alicia Robb and Joseph Farhat for providing the codes for primary owners.

GATE experiment is the largest-ever randomized evaluation of entrepreneurship training and assistance involving more than 4,000 participants. It differs from earlier large-scale evaluations in the United States because its training was marketed to any individual interested in starting or growing a business, and was not limited to individuals receiving unemployment or welfare benefits. It also involved both individuals who wanted to start a business and individuals who already owned a business, but wanted to grow that business.

GATE was administered between September 2003 and July 2005 in cities of varying sizes: Philadelphia; Pittsburgh; Minneapolis/St. Paul; Duluth, Minnesota; Virginia, Minnesota; Portland, Maine; Lewiston, Maine; and Bangor, Maine (see Bellotti et al. 2006 for more details). Both urban and rural populations were served by the sites. Fourteen different organizations provided the GATE training, including SBA-funded Small Business Development Centers and non-profit community-based organizations. All of the providers and their programs had been operating prior to the experiment, and thus collectively represent the existing market for entrepreneurship training in the United States.

Individuals interested in applying to receive entrepreneurship training through the program had to first attend an orientation meeting at a One-Stop Career Center. Applicants were informed that "GATE does not have space for everyone" and that a "lottery or random drawing will decide whether you will be able to enter the program." Applicants were then randomly assigned to the treatment or control group with equal probability. The treatment group was offered an array of free services. Program administrators informed the control group that the GATE program did not have the capacity to offer them services, and administrators offered no referrals to other (free) services either.

The array of GATE services offered to the treatment group began with a one-on-one assessment meeting to determine an individual's specific training needs. Then training was provided by experienced business consultants in classroom and/or one-on-one settings. Classroom offerings targeted a variety of general and specialized topics at different experience levels. Introductory courses cover subjects such as legal structure, business plans, and marketing. Intermediate and advanced courses cover subjects including managing growth, legal risks, and personnel issues. These classes would be especially important for entrepreneurs deciding whether to hire their first employee. The total cost of providing training to GATE recipients was estimated to be $1,321 per person.

Extensive data were collected on treatment and control group members on the application survey and from three follow-up surveys. Data are available at baseline (prior to entrepreneurship training) and at follow-up waves of 6 months, 18 months and 60 months after baseline. Detailed information on employment, sales, profits and other firm characteristics are available for each time period. Detailed information on owner characteristics such as age, education, gender, race, immigrant status, marital status, children, family income, health, family business experience, credit history, unemployment insurance receipt, health insurance, and personality traits are also available from the baseline survey. The resulting dataset provides unprecedented longitudinal information on the employment of businesses after the owners of those businesses received training. The impact of entrepreneurship training on when and whether businesses hire their first employee has not been previously examined.

In the experiment, 4,197 individuals completed the application process and were randomly assigned to the treatment (N=2,094) or control (N=2,103) group. Among participants, 19 percent were self-employed business owners at the time of application (N=774), and 44 percent of the businesses owned reported not ever having employees (N=343). For this study, the focus is on these non-employer business owners participating in the experiment. Previous research on the full sample of participants generally finds small or no effects of entrepreneurship training on outcomes (Benus et al. 2009; Fairlie, Karlan and Zinman 2015), but these studies do not estimate the effects of entrepreneurship training on hiring the first employee among the group of non-employer business owners participating in the experiment. This analysis provides the first evidence in the literature on this question.

3. Hiring Dynamics among Non-Employer Startups

We first examine the dynamic patterns of hiring employees among startups. The panels of non-employer startups included in the iLBD and KFS are important because all firms can be tracked even if they are not successful in the first few years after startup. Cross-sectional data based on existing non-employer and employer firms include only surviving firms up to that point in time and all non-surviving firms when they hired their first employee. Also retrospective information on when the first employee was hired instead of contemporaneous information is more subject to the possibility of recall bias.

We start by examining patterns of hiring among non-employer startups in the universe of non-employers provided in the iLBD. Our definition of a non-employer startup is any firm that has no record of existing for the previous three years. The first year observed is defined as the startup year. We include the complete universe of non-employer firms across all industries, revenues and business types. When a business is identified in a subsequent year in the employer data base we define that year as the point when the first employee is hired. It is important to note that there can be slippage in the match from non-employer to employer because the datasets are generated from different sources.[9] We view these results as a lower bound on the level of transitions from non-employers to employers.

Table 1.A reports the distribution of all non-employer startups across hiring their first employee in up to seven follow-up years, not hiring their first employee by the end of the seven-year period, or exiting before hiring an employee during the seven period. This provides detail on when non-employer startups hire their first employee. For example, it answers the question of what percentage of businesses hire their first employee in the first year after startup vs. the second year after startup. Among all non-employer startups, 2 percent hire their first employee in the first year after startup. Very low percentages of non-employer startups hire their first employee after that year. A large percentage of non-employer startups (12.7 percent), however, do not hire their first employee by the end of the seven-year period. Finally, 84.8 percent of non-employer startups exited over the sample period before ever hiring their first employee. But, it is important to note here that exits are defined as non-employers that do not report revenues in year 7 (and thus are not in the non-employer universe that year). These non-employers could report revenues and be in the universe of non-employers in later years, but this is out of our sample period. This could explain the extremely high exit rate as we have defined it here and this should not be interpreted as a business failure rate for non-employer businesses.

A very large percentage of these non-employer businesses are consulting, contracting or small-scale business activities. When we focus on different types of non-employer startups we find much higher rates of hiring employees. For example, Table 1.B includes only EIN cases for non-employer startups. These are businesses that are identified through filing for an EIN even

[9] The linkage between the non-employer and the employer universes makes use of the name of the business and the tax identifiers; the EIN and the SSN. If any of these change then we might not be able to form a link. This is more likely when there is a change in legal form of organization at the time of the transition.

though they do not have employees. Another example, is Table 1.C which includes only incorporated non-employer startups. In both cases, transition rates from non-employer to employer are much higher although most of the transitions are occurring in the first few years and there continues to be a very high exit rate (or non-existence rate in year 7).

The iLBD contains a very large number of non-employer businesses that have very low revenues. Focusing on higher revenue non-employer startups we find higher rates of transitions to employment. But, focusing on revenues in the first year can be problematic as many potentially successful businesses take a few years to produce sales.

These aggregate measures of hiring employees in the first several years following startup reveal interesting patterns. Many non-employer startups hire their first employee in the first three years of existence. After that period of time and through seven years, only a few additional firms make the switch from non-employer to employer.

Hiring Patterns in the KFS

We turn to the KFS for a similar analysis of patterns of hiring among non-employer startups. The KFS, which is based on D&B data, is known to include businesses that are more growth and employment oriented than the universe of non-employers. With this in mind, we also examine patterns of hiring in these data before turning to an analysis of the determinants of hiring. The KFS is crucial to examining determinants because it contains detailed information on owner and business characteristics. The iLBD, unfortunately, is limited to including only a few pieces of administrative information on businesses. Also, the KFS implicitly rules out the many non-employer startups that are essentially consulting and small-scale business activities by individuals with no intention of growing a business and eventually hiring employees. Thus, the inclusion of this group is problematic for exploring the owner and business characteristics associated with hiring employees. With this in mind we turn to a detailed analysis of the KFS data that include more growth- or employment-oriented non-employer startups.

To better illustrate the KFS panel, Appendix Figure 1 displays the full sequence of hiring decisions over the first seven years using data from the KFS. The KFS includes information through seven years following startup.[10] Starting with the first year, there were 2,460 non-employer startups in the KFS with complete information on employment decisions that year. Of those non-employer businesses, 38.0 percent hired their first employee and 7.4 percent went out of business that year. Of the 1,197 businesses remaining as non-employers in the KFS in the second year, 26.0 percent hired their first employee and 9.5 percent went out of business in that year. In the following years, the probability of hiring the first employee drops as the remaining sample of non-employer businesses becomes smaller. The percentage of non-employer businesses going out of business each year, however, does not decline.

Table 2.A reports the distribution of non-employer startups across hiring their first employee in one of the seven follow-up years, not hiring their first employee by the end of the seven-year period, or going out of business before hiring an employee. This provides detail on when non-employer startups hire their first employee, summarizing the information displayed in Appendix Figure 1. Firms that are known to go out of business before hiring an employee by the reported year are included in the sample, implying that the estimates are not conditional on survival to that year. But, only businesses with complete information on employment and survival through all seven years are included to avoid biasing estimates for earlier years. Among the more growth-oriented non-employer startups captured in the KFS, 36.6 percent hire their first

[10] The reported estimates are only for non-employer startups. Startups with employees represent 40.9 percent of all startups captured in the KFS.

employee in the first year after startup. 12.6 percent of startups hire their first employee in the second follow-up year, and 4.0 percent hire in the third follow-up year, and 3.1 percent hire in the fourth follow-up year. Only a small percentage of non-employer startups hire their first employee in the fifth, sixth or seventh years following startup. A large percentage of non-employer startups (13.3 percent), however, are still in business, but do not hire their first employee by the end of the study period. Finally, 27.9 percent of non-employer startups went out of business over the sample period before ever hiring their first employee.

Another method of measuring when non-employer startups make the switch to an employer firm is to examine the likelihood of hiring the first employee *by* each of the follow-up years. Table 2.B reports estimates. Again, firms that are known to go out of business before hiring an employee are included in the sample so the estimates are not conditional on survival. But, in this case we use the maximum number of observations available to calculate the probability for each year (which is why the sample size declines with more years available). One year after startup, 38.0 percent of non-employer startups in the KFS have hired their first employee. By two years after startup the majority of non-employer firms have hired their first employee.[11] By seven years after startup, 58.8 percent of initial non-employer businesses have hired their first employee.[12] The increase in the likelihood of hiring a first employee rises quickly and then slows down as more businesses have already hired their first employee.

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[11] The sample size drops for 2 years after startup and each subsequent year because some businesses have missing information on employment in those years. Estimates of hire rates by follow-up year conditioning on only businesses with non-missing observations for all survey years are similar.

[12] Annual sample attrition rates are 1 to 4.5 percent per year which contributes to losing observations over time, but another issue is that even if one missing value is found for employment in an intermediate year it cannot be used to calculate the seven year cumulative probability. Thus, some caution is needed in interpreting the 7-year out estimates.

Although hiring rates among more growth- or employment-oriented non-employer startups in the KFS are higher than hiring rates among the universe of non-employer startups, the general patterns are similar. Most non-employer startups that will eventually hire an employee, hire their first employee in the first few years of existence (and especially in the first year). After that period of time and through seven years, only a small percentage of additional firms make the switch from non-employer to employer.

4. Demographic and Human Capital Characteristics of Entrepreneurs

This section examines the demographic and human capital characteristics of the owners of non-employer businesses that lead to hiring their first employee. As noted above, the KFS is the only large, nationally representative dataset with detailed demographic and human capital information on the owners of startups.

We first examine rates of hiring an employee in the first several years of operation among non-employer startups by race, gender and immigrant status. Table 3 reports estimates of the percentage of non-employer startups hiring employees by 1, 2 and 7 years after startup. These years are chosen to represent a wide range of hiring points over the sample period. Estimates from the KFS indicate that non-employer startups owned by African-Americans have similar rates of hiring their first employee by each year as do white, non-Hispanic startups. Asian-owned startups have higher rates of hiring their first employee by each of the follow-up years. Hiring rates by each follow-up year are also higher among non-employer startups owned by Hispanics. Related to these racial and ethnic patterns, immigrants have higher rates of hiring their first employee by the first two follow-up years than the native-born, but the rates of hiring employees are similar by the seventh follow-up year.

Non-employer startups owned by men and women differ substantially in their rate of hiring first employees by each of the reported follow-up years. Female-owned startups are roughly 10 percentage points less likely to hire their first employee by the first, second and seventh years after startup.

To investigate these patterns further and control for potential correlations with other entrepreneur characteristics we estimate regressions for the probability of hiring employees by each survey wave. The regression equation is:

(4.1) $y_i = \alpha + \beta X_i + \varepsilon_i$,

where y_i is the probability that the non-employer startup hires its first employee by the first, second or seventh follow-up year. X_i includes demographic and human capital characteristics of the entrepreneur, and ε_i is an error term. All specifications are estimated using OLS and heteroscadasticity-consistent standard errors are reported. Marginal effects estimates are similar from probit and logit models, and are thus not reported.

Table 4 reports estimates. Non-employer businesses owned by Asians, other race, and Hispanics have higher probabilities of hiring their first employee than non-Hispanic, white-owned businesses, all else equal. Non-employer firms owned by African-Americans have similar likelihoods of hiring their first employee as non-Hispanic whites. Immigrant status also does not appear to have an effect on hiring probabilities after controlling for other entrepreneur characteristics. Female-owned non-employer firms have lower annual probabilities of hiring their first employee than male-owned firms.

Turning to the human capital of the entrepreneur, we include the owner's level of education as a set of dummy variables for thresholds in the regressions. As noted above, owner's education has been found to be a positive predictor of hiring employees, but the relationship with early stage hiring patterns are unknown. Surprisingly, estimates from the KFS do not provide evidence that among non-employer startups owner's education has a strong positive predictive power on whether the first employee is hired in the first several years of operation. The point estimates are generally small and statistically insignificant and in a couple of cases negative.

Another measure of human capital – having more industry work experience before startup – is found to have a positive, but weak relationship with hiring an employee in the first several years of operation. Previous industry work experience has been found to be an important determinant of business success in previous work (e.g. see Fairlie and Robb 2007). Unfortunately, the KFS does not include contemporaneous information on wage and salary work of owners which has also been found to be important (Garcia-Perez, Goetz, Haltiwanger and Sandusky 2013).

Although human capital, such as owner's education and prior industry work experience, has been identified as an important determinant of business success in previous research, it appears to be less important in determining which non-employer startups hire their first employee in the first several years of operation.

In contrast to the human capital measures, we find that industry differences are important in determining which non-employer startups are likely to hire employees.[13] Non-employer startups in wholesale trade have the highest rate of hiring employees, followed by the

[13] Hiring rates by industry are reported in Appendix Table 2.

transportation, manufacturing and professional industries. In these industries, hiring employees may be important for capturing returns-to-scale for growth of businesses.

Legal Form of Organization

The KFS also includes information on the legal form of organization of the business. Does the legal form of organization affect the probability of hiring an employee among non-employer startups? This question is examined by estimating the same set of regressions including dummy variables for the legal form of organization. Dummy variables are included for incorporated businesses (58.6 percent) and partnerships (5.5 percent). Estimates are reported in Table 5. Non-employer startups that are incorporated are more likely to hire their first employee by each of the reported follow-up years relative to non-employer startups that are sole proprietorships. The evidence is less clear for partnerships. The interpretation of these results is difficult because decisions about employment might cause businesses to choose their legal status. For example, a non-employer startup that plans on hiring employees in the first few years might choose to become incorporated because of the employment decision. Additionally, a relatively small percentage of firms change legal form status, suggesting that becoming incorporated is not a potentially important milestone such as revenues or assets (Cole 2011). The estimates for the demographic and human capital characteristics are not sensitive to the inclusion of the legal form of organization variables.

5. Dynamic Business Milestones Associated with Hiring the First Employee

Continuing to use the KFS, we switch the focus to exploring the dynamic business factors associated with hiring decisions. An important question is whether there are milestones that non-employer startups often reach before hiring their first employee. For example, non-employer firms might often wait until they have large enough annual revenues to take on the extra expenses of hiring employees. Do startups wait to build up assets or obtain intellectual property before hiring their first employee?

The examination of these questions requires longitudinal data on startups with measures of both employment and milestone variables year by year instead of a single point in time. By combining follow-up years to create a panel it is possible to measure the annual probability that non-employer firms hire their first employee over the entire sample period. It is also possible to measure levels of revenues and business assets of non-employer firms prior to the timing of the employment decision. Table 6 reports an estimate of the annual probability of hiring the first employee among non-employer firms.

Estimates of annual hire rates are also reported by revenue class in Table 6. Perhaps surprisingly, the likelihood of hiring the first employee is not strongly related to total business revenues. The probability of hiring an employee actually decreases by 8.1 percentage points from non-employer firms with $0 in annual revenues to non-employer firms with $1-$10,000 in annual revenues. The likelihood of becoming an employer firm remains steady as revenues increase until the $100,001 or more level. For revenues of $100,001 or more, the probability of hiring the first employee in the next year increases by 9 percentage points from non-employers with revenues of $25,001-$100,000.[14] Even this change is not large considering the potential importance of higher revenues to offset the increased costs of hiring employees.

Table 6 also reports estimates by business asset levels. Assets include cash, accounts receivable, equipment, machinery, product inventory, and vehicles. Non-employer startups may

[14] Only categorical information on revenues is available in the KFS.

wait until their business assets hit a certain level to offer financing or collateral for raising money to hire employees. Similar to revenue levels, however, there is no clear evidence that the probability of a non-employer firm hiring its first employee over the following year increases substantially with business asset levels. The probability that a non-employer business with $0 in total business assets hires its first employee over the following year is 22.0 percent. For non-employers with $100,001 or more in total business assets the probability is not much higher. Non-employers with $25,001-$100,000 in total business assets have a probability that is 4 percentage points higher.

Both business revenues and assets measure the current resources of the firm, but future potential resources of the firm may be the most important in making the decision to become an employer firm. In particular, a milestone for many non-employer startups might be when they obtain intellectual property, such as a patent, trademark or copyright. Patents, trademarks and copyrights might be useful for non-employer firms considering hiring employees because they provide a potential source of future revenues even if the firm is experiencing low current revenues. For non-employer firms with patents, the probability of hiring the first employee increases by 8.6 percentage points (see Table 6). Obtaining copyrights and trademarks is also associated with an increase in the likelihood of becoming an employer firm: for copyrights the increase is roughly 5 percentage points; for trademarks, 13 percentage points. Combining all types of measurable intellectual property, the estimates indicate that having at least one type is associated with roughly a 9 percentage point higher rate of hiring the first employee.

To identify the independent associations between these milestones and the decision to hire the first employee, we estimate several regressions for the probability of hiring employees. The regression equation is:

$$(5.1)\ y_{it} = \alpha + \beta X_i + \gamma Z_{it-1} + u_i + \varepsilon_{it},$$

where y_{it} is whether the entrepreneur hires in year t, X_i includes entrepreneur characteristics that do not change over time, Z_{it-1} include business characteristics that change over time (measured prior to the employment decision), and $u_i + \varepsilon_{it}$ is the composite error term. The observational unit in the regressions is the business year, and only startups that have not previously hired an employee up to that year are included in the sample. All specifications are estimated using OLS and robust standard errors are reported with adjustments for multiple observations per entrepreneur (i.e. clustered by entrepreneur). Marginal effects estimates are similar from probit and logit models, and are thus not reported.

Table 7 reports estimates. Specification 1 focuses on the independent effects of owner characteristics and industries on the annual probability of hiring the first employee. The estimates reveal similar patterns as those for the regressions predicting hiring the first employee by 1, 2 and 7 years following startup. Asians, other race and Latino non-employers have higher rates of making the transition to an employer firm than do non-Hispanic, white and black non-employers. Female-owned businesses have a lower annual probability of hiring the first employee over the sample period than male-owned businesses. The education level of the entrepreneur has no effect on the hiring probability, but entrepreneurs with more prior work experience have a higher annual probability of hiring the first employee.

Specification 2 adds the dynamic business milestone variables reported in Table 7 to the regression specification. In addition to these milestone variables, the regression includes all of the previous owner characteristics, industry, and regional controls. After controlling for other factors, there does not appear to be a strong, clear relationship between revenues and the probability of hiring the first employee. Most of the coefficients on revenue levels are negative, indicating that non-employer businesses with zero revenues have relatively high probabilities of hiring their first employee in the sample period (the left out or comparison category is zero revenues). There is some evidence, however, that the largest revenue class has a higher probability of hiring the first employee than the previous revenue classes, indicating a somewhat U-shaped relationship.

The estimates for business assets, however, indicate a positive relationship with the annual employment probability. An increase in the probability of hiring the first employee occurs when firms have business assets of $10,001 to $25,000. After that level there is no further increase, but firms with at least $10,001 in business assets have a 6-9 percentage point higher probability of hiring the first employee over the sample period, all else equal.

Having intellectual property also has a positive association with making the non-employer to employer transition during the sample period. Intellectual property, which includes patents, copyrights and trademarks, is associated with a 7 percentage point increase in the annual probability of hiring the first employee.

Although not reported, regression specifications are estimated that include all three types separately. Including all three types of intellectual property separately in the regression, estimates indicate that the strongest relationship is between trademarks and the annual probability of hiring the first employee.

Revenues and business assets are positively correlated, which might weaken their estimated relationships with the employment probability. Specifications 3 and 4 include revenues and assets alone with the other controls, respectively. The estimates confirm the conclusion from the previous regressions – business assets have a positive association with the probability of hiring the first employee, but revenues do not have a clear relationship. It may be more important for non-employer firms to build up assets to use or borrow against to hire their first employee than to rely on large revenues in the previous year.

Although all of these dynamic business milestones are measured when the business has no current employees, there remains the concern that the estimated effects are not causal. This is an important concern with the regression results. The positive relationship between business assets and hiring the first employee might simply represent the unobserved growth plan of the business and not that higher assets *cause* non-employer firms to take the leap to being an employer firm. The same concern arises for intellectual property. Although it is measured for the business prior to hiring their first employee, estimates of the relationship might capture other unobserved factors. The finding that revenues do not have a clear positive relationship with the annual employment probability is less a concern, however, because the likely bias is towards finding a positive relationship. Without an instrument for revenues, these results do not provide definitive estimates on the causal effects of reaching milestones on hiring the first employee.[15]

Businesses with Positive Revenues

There is often concern that the behavior of businesses that have no revenues might differ substantially from businesses with positive revenues. To examine this potential concern, we first compare the characteristics of zero-revenue observations to positive-revenue observations among non-employer startups. Appendix Table 3 reports estimates. The owner and firm characteristics

[15] In this application it is extremely difficult to find an instrumental variable that has an effect on the sales of the business, but does have an effect on the unobserved component of the decision to hire the first employee. Similarly, an experiment that randomly varies revenues, assets and intellectual property would be infeasible.

of zero-revenue observations for startups do not appear that different than positive-revenue observations. Demographic, education and work experience characteristics of the owner do not look that different (except along a few expected characteristics such as black firms having lower revenues). The industry distributions for zero and positive revenue startups also look relatively similar. There are lots of zero-revenue startup observations that hire employees the next year (27% compared with 22% of positive-revenue observations), and that have intellectual property (15% compared with 14%).[16]

Although there do not appear to be major differences by zero vs positive revenue observations, we nevertheless, estimate regressions excluding those observations as a robustness check. Table 8 reports estimates of the same set of regressions excluding all business observations with zero revenues. Including only positive revenue non-employer startup observations reduces the sample size by roughly one-third. The estimates for the owner characteristics, such as Asian, Hispanic, female and industry work experience are similar. The estimates for intellectual property are also generally similar.

The estimates for revenues and business assets reveal some interesting patterns. First, there is some evidence of a positive relationship for the largest revenue class relative to the $1-10,000 revenue class. This finding is similar to previous findings, but highlighted somewhat by the change in the reference from the $0 revenue class in Table 7 to the $1-10,000 revenue class in Table 8.[17] There is no evidence of a positive relationship across the other revenue classes. Second, the estimates indicate a stronger positive relationship between business assets and hiring

[16] Another interesting finding is that slightly more than 50% of non-employer startups with zero revenues in one year have positive revenues the following year. Roughly 15% of non-employer startups with positive revenues follow that year with zero revenues. There appears to be some transitioning back and forth between not having revenues and having revenues among non-employer startups.
[17] The change in left-out category from Table 7 to Table 8 essentially removes the left part of the U-shaped relationship.

first employees. The removal of zero revenue observations has increased all of the coefficient estimates. Finally, similar to previous findings, estimates of the relationship between business assets and hiring probabilities are not sensitive to the inclusion or exclusion of the revenue variables. Overall, the results excluding zero-revenue observations do not change the general conclusions.

Services and Other Industries

The relationships between revenues and business assets might differ across industries. The KFS sample is not large enough to run separate analyses by detailed industry, but it is large enough to run separate regressions for broad industry groupings. Table 9 reports estimates for regressions including only non-employer startups in the services industry (where many startups are found). Table 10 reports estimates for regressions including only non-employer startups in the construction, manufacturing, trade, and other industries. In the services industries, the relationship between sales and hiring is not clear. The relationship between business assets and hiring is also not clear, although there are some positive coefficients relative to the lowest level. Only a few of the coefficient estimates are statistically significant, which is in part due to smaller sample sizes.

In the regressions that include the construction, manufacturing, trade and other industries, the positive relationship between business assets and hiring probabilities is clear. Hiring increases generally with each level of business assets. The relationship with revenues is less clear, with hiring first decreasing with higher sales and then increasing for these industries. The separate industry analyses, in general, do not reveal different patterns for the revenues and business asset results than for the main results.

Estimates for the other variables indicate that intellectual property has a similar association with hiring in the two broad industry groups. The industry groups also have similar demographic characteristics predicting which non-employer startups hire. Although it would be useful to conduct separate analyses with more detailed industries, the results for these broad groupings do not indicate substantially different results and the sample sizes are not large enough in the KFS to investigate the question further.

6. Does Entrepreneurship Training Help Owners Hire Their First Employee?

Returning to the question of whether the human capital of the entrepreneur is important for hiring decisions, we examine whether entrepreneurship training can help overcome some of the barriers to hiring employees. Entrepreneurship training often specifically teaches self-employed business owners strategies for hiring and managing employees, and provides training on registering for EINs, tax and insurance compliance, and legal issues, but does it increase the likelihood of hiring the first employee? Data from the largest random experiment providing entrepreneurship training—the GATE experiment—are used to examine this question.

As noted above, the analysis focuses on the participants in the GATE experiment who were self-employed business owners at the time of application and reported not ever having employees for their businesses. Thus, the experiment is used to estimate the effects of entrepreneurship training on non-employer entrepreneurs hiring their first employee.

Table 11 starts by comparing mean baseline characteristics between the treatment and control groups to check the randomization. The groups appear to be similar. Among the numerous baseline characteristics measured in the application none are statistically different between the treatment and control groups. Even though we do not detect any differences, in the estimates of treatment effects, results are presented both without controls and with controls for a large set of detailed baseline characteristics.

With any random experiment, the control group cannot be restricted from obtaining training elsewhere. They cannot receive free services through the GATE program, but they can seek assistance through the existing market for training services. Given this limitation with any training experiment, it is important to examine whether and how the GATE treatment actually changed the use of training services. Table 12 reports the percentage of participants receiving entrepreneurship training and the mean hours of training separately for the two main types of training: classroom, workshops and seminars, and one-on-one counseling or technical assistance. The treatment group was an estimated 32 percentage points more likely to receive any training in the 6 months following random assignment than the control group. The first 6 months after random assignment was the most intensive period for receiving training, with less training received during the subsequent 12-month period (i.e. between Wave 1 and Wave 2) and the last 12-month period (i.e. before Wave 3).

The treatment group also received more than twice the number of hours of training by the first follow-up wave. The difference in training received is 9 hours at Wave 1 and summing across waves. The extra hours of instructional time are likely to result in substantially more "homework" time. Although students learn or receive guidance in the classroom or one-on-one counseling, research and calculations for planning and strategies for business growth are done elsewhere, and thus not reported as “training” hours. Among those who received any training, the treatment group received on average 21.0 hours of training in the first 6 months, which is roughly two-thirds the instructional time for a 5-unit college course over a quarter.

Follow-up survey responses also indicate that GATE participants were satisfied with services. Table 13 reports estimates for the treatment and control groups who received services. 48.6 percent of GATE recipients reported that “the overall usefulness” of the services received was “very useful,” with 31.3 percent responding “somewhat useful.” Most recipients of GATE training responded that services helped “a lot” or “somewhat” with at least one specific aspect of the business or business planning (e.g., marketing strategy, accounting, networking, information technology). The treatment group reported greater satisfaction overall, and for each of the training aspects, than control group trainees (who obtained non-GATE training of their own accord). One interesting finding is that a low percentage of the treatment group (and control group) reported that the entrepreneurship training they received helped "a lot" with "hiring and dealing with employees" relative to other areas in which it helped. Of course, this may mean they were not looking for this kind of help, rather than that the training was not useful for hiring employees. Furthermore, these results must be interpreted with caution because they are only suggestive self-reports of how areas of training helped participants.

Estimating the Effects of Entrepreneurship Training on Hiring the First Employee

I next examine the effects of entrepreneurship training on non-employer business owners hiring their first employee. The regression equation for the employment outcome, y_i , in the context of the random experiment is straightforward:

(6.1) $y_i = \alpha + \delta T_i + \gamma X_i + \varepsilon_i$.

where T_i is the treatment indicator, X_i includes all of the baseline covariates reported in Table 11, and ε_i is an error term. The effect of becoming eligible for entrepreneurship training through the GATE program or the "intent-to-treat" (ITT) estimate of the training program is captured by δ. Measures of employment at three follow-up waves after random assignment are available: Wave 1 at 6 months, Wave 2 at 18 months, and Wave 3 at 60 months. Employment at each of the waves is examined for the sample of non-employer firms participating in the experiment.

Table 14 reports estimates from (6.1) of the effects of entrepreneurship training through the GATE program on employment. In the first panel, the treatment effects on the probability of hiring the first employee by each of the follow-up waves are reported. The sample includes only business owners with no employees at the time they applied to the GATE program. This is the time of random assignment. The first column does not include any controls, and thus essentially calculates the difference in employment rates between treatment and control groups in the experiment. At Wave 1, 11.6 percent of the treatment group and 8.8 percent of the control group hired an employee for a difference of 2.8 percentage points. The estimated treatment-control difference, however, is not statistically significant.

Table 14 also reports specifications that include controls and that are for additional follow-up waves. None of the point estimates for the entrepreneurship training treatment effects on hiring the first employee are statistically significant. These results are consistent for the 6-month, 18-month and 60-month follow-up periods.

Table 14 also reports estimates of the effects of entrepreneurship training on current employment at the point in time of each follow-up survey. In the second panel, the effects on the probability of hiring an employee *at* each of the follow-up waves are reported. The 6-month or Wave 1 results are the same as those reported in Panel 1 because Wave 1 is the first follow-up survey. At the 18-month and 60-month periods, the point estimates are no longer positive. They remain statistically insignificant. In both specifications and across follow-up waves, insignificant estimates and inconsistent signs on those estimates are found. Thus, there is no evidence of a positive effect of entrepreneurship training on increasing the likelihood that non-employer business owners hired an employee at each of the follow-up surveys.

Although entrepreneurship training through the GATE program does not increase the likelihood a non-employer firm hires an employee at each follow-up wave, it might increase overall employment levels. In the second panel, the entrepreneurship training treatment effects on number of employees for non-employer business owners at each follow-up wave are investigated. Similarly, there is no evidence of positive effects of entrepreneurship training on the number of employees.

The lack of effects on entrepreneurship training on hiring employees does not appear to be due to differential rates of non-employer businesses ceasing operations over the study period. If a business stops operating, then technically it cannot hire employees. The estimates do not condition on survival because that could introduce a bias in estimating the effects of entrepreneurship training through the experiment.

Table 15 reports estimates of the effects of entrepreneurship training on whether the non-employer business owner at baseline continues owning a business at each of the follow-up waves. There is some drop-off in business ownership, as roughly 20 percent are no longer business owners at Wave 1, 28 percent at Wave 2, and 33 percent at Wave 3. The estimates, however, do not provide any clear and consistent evidence that entrepreneurship training increases the likelihood that non-employer business owners remain in business.

These results are also consistent with lack of evidence of an effect of entrepreneurship training on the sales of businesses owned by initial non-employer owners. Estimates are reported in Table 15. There is no evidence of a positive effect of entrepreneurship training on sales.

All of the experimental estimates reported thus far capture the "intent-to-treat" or the effects of the offer of entrepreneurship training through the GATE program. Another commonly reported estimate in an experimental setting is the local average treatment effect (LATE). LATE shifts the focus from estimating the effects of the *offer* of entrepreneurship training on hiring employees to estimating the effects of *receiving* entrepreneurship training on hiring employees. The estimation involves using instrumental variables, which is operationalized by using 2SLS. In the first stage the probability of receiving any entrepreneurship training is regressed on treatment (the instrument). In the second stage, employment is regressed on the predicted value of receiving any entrepreneurship training from the first stage. The technique scales up the ITT estimate by dividing it by the difference between the percentage of the treatment group receiving any training and the percentage of the control group receiving any training. It adjusts the treatment-control difference estimate upward to account for the fact that it was originally calculated with only part of the treatment group receiving training and part of the control group not receiving training.[18] As reported in Table 12, 86 percent of the treatment group did not receive any entrepreneurship training in the first 6 months after random assignment, and 54 percent of the control group received at least some entrepreneurship training (outside of GATE) in the 6 months after random assignment (e.g. 0.86-054=0.32 for the 6-month survey).

Appendix Table 4 reports LATE estimates for the three employment outcomes reported in Table 14. The reported estimates are larger, but not statistically significant for any measure or

[18] LATE estimates, however, have two well-known drawbacks. First, LATE only provides an estimate of the effect of receipt of entrepreneurship training for those individuals complying with the experiment (i.e. the treatment group who received entrepreneurship training and the control group who did not receive entrepreneurship training). LATE estimates are then interpreted as "local" estimates of the effects of entrepreneurship training for compliers. Second, they rely on the key assumption that the receipt of any entrepreneurship training means the same thing for the treatment and control groups (otherwise the rescaling up of the ITT estimate would be invalid). This is problematic here if the control group is receiving a very different quality and level of services on average than the treatment group.

any follow-up survey. The main conclusion does not change – we find no evidence that entrepreneurship training increases the likelihood of hiring employees among non-employer entrepreneurs.

7. Conclusions

From the analysis of longitudinal data from the iLBD, several interesting patterns emerge regarding the dynamics of non-employer startups hiring their first employee. Among business hiring employees, a large percentage of non-employer startups hire their first employee in the first three years of existence, with only a small percentage hiring their first employee in the few years after that period. Hiring patterns over time are roughly similar in the KFS sample of non-employer startups, but higher because of the more growth- and employment-oriented businesses contained in the underlying D&B data.

The likelihood of making the transition from non-employer to employer business within the first several years of operation differs by the race, ethnicity and gender of the entrepreneur. Non-employer businesses owned by Asians and Hispanics have higher probabilities of hiring their first employee than white-owned businesses, all else equal. Non-employer firms owned by African-Americans have similar likelihoods of hiring their first employee as whites. Female-owned non-employer firms have lower annual probabilities of hiring their first employee than male-owned firms.

The entrepreneur's human capital, measured as owner's education and prior industry work experience, does not strongly predict hiring the first employee, although there is some evidence of a positive relationship with prior industry work experience. Data from the GATE experiment is used to examine the question of whether entrepreneurship training increases the likelihood that non-employer entrepreneurs hire an employee within the next several years. We find do not find evidence of positive effects of entrepreneurship training on hiring the first employee by 6, 18 and 60 months. Furthermore, the estimates do not provide evidence that the probability of hiring an employee or the number of employees increases with entrepreneurship training. Entrepreneurship training, however, might be more effective for business owners in specific industries or with specific backgrounds. More research with larger samples of non-employer business owners is needed to explore this question.

Using the longitudinal data from the KFS, another important question examined is whether there are milestones that non-employer startups often reach before hiring their first employee. Surprisingly, we do not find clear evidence of a strong relationship between the revenues of non-employer firms and the decision to hire their first employee in the KFS sample. The evidence, however, is less ambiguous that higher levels of business assets are associated with non-employer businesses making the transition to employer firms. It may be important for non-employer firms to build up assets to use or borrow against to hire their first employee. Having intellectual property also has a positive association with making the non-employer to employer transition during the sample period. Intellectual property, which includes patents, copyrights and trademarks, is associated with a 7 percentage point increase in the annual probability of hiring the first employee. Intellectual property may be valuable for securing future revenues for hiring employees.

The analysis of iLBD, KFS and GATE experimental data represents one of the detailed studies on the topic of what predicts whether and when an entrepreneur hires the first employee. Although some caution is warranted in interpreting the estimates they represent an important first step towards better understanding the determinants of entrepreneurs making the decision to take the leap from non-employer to employer firms. More research on the important topic of job creation by entrepreneurs is clearly needed.

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Appendix Table 1: Industry Distribution of Non-Employer Startups in Kauffman Firm Survey (2004), Non-Employer Startups in iLBD (2004), and New Non-Employer Firms in Survey of Business Owners (2007)

	Non-Employer Startups (KFS 2004)		Non-Employer Startups (iLBD 2004)		New Non-Employers (SBO 2007)	
Industry	Percent	N	Percent	N	Percent	N
Other industries	1.4%	2838	2.0%	5543283	1.2%	151113
Construction	12.1%	2838	12.4%	5543283	11.2%	151113
Manufacturing	5.8%	2838	1.4%	5543283	1.5%	151113
Wholesale trade	5.6%	2838	1.8%	5543283	1.8%	151113
Retail trade	13.6%	2838	10.0%	5543283	9.8%	151113
Transportation and warehousing	2.7%	2838	4.6%	5543283	4.9%	151113
Information	3.4%	2838	1.9%	5543283	1.9%	151113
Finance, insurance and real estate	10.9%	2838	12.3%	5543283	11.5%	151113
Professional services	17.0%	2838	13.5%	5543283	18.0%	151113
Management	10.1%	2838	7.7%	5543283	8.9%	151113
Health and educational services	3.4%	2838	12.3%	5543283	12.0%	151113
Entertainment, accommodation and food services	3.9%	2838	6.3%	5543283	6.3%	151113
Other services	10.3%	2838	13.9%	5543283	11.1%	151113

Notes: (1) The KFS sample consists of businesses with no employees at startup in 2004. (2) The iLBD consists of the universe of non-employer startups. (3) The SBO sample consists of businesses with no employees staring in 2006 or 2007. (4) Sample weights are used for the KFS and SBO estimates.

Appendix Table 2: Industries and Hiring Rates of First Employee among Non-Employer Startups
Kauffman Firm Survey (2004-2011)

	by 1 Year after Startup		by 2 Years after Startup		by 7 Years after Startup	
Industry	Percent	N	Percent	N	Percent	N
Other industries	26.4%	26	39.7%	26	38.3%	12
Construction	42.2%	197	59.6%	171	79.4%	77
Manufacturing	45.4%	375	61.1%	250	76.2%	111
Wholesale trade	55.1%	88	69.6%	88	88.1%	44
Retail trade	36.9%	240	53.2%	205	73.6%	78
Transportation and warehousing	39.1%	49	69.4%	44	90.0%	19
Information	31.0%	95	54.8%	77	59.9%	42
Finance, insurance and real estate	25.0%	177	42.4%	163	59.2%	72
Professional services	43.5%	647	59.3%	552	78.0%	290
Management	40.2%	200	64.8%	149	80.7%	68
Health and educational services	37.5%	59	56.7%	55	79.2%	23
Entertainment, accommod. and food services	29.2%	80	49.8%	59	59.8%	36
Other services	30.3%	227	50.2%	193	66.8%	82

Note: The sample consists of businesses with no employees at startup in 2004.

Appendix Table 3: Owner and Firm Characteristics among Zero- and Positive-Revenue Non-Employer Startups
Kauffman Firm Survey (2004-2011)

Owner Characteristic	Zero Revenue Observations	Positive Revenue Observations
White, non-Hispanic	73.2%	88.2%
African-American	17.3%	5.6%
Asian-American	3.7%	2.1%
Other race	5.4%	3.5%
Hispanic	4.7%	3.4%
Immigrant	9.6%	6.7%
Female	33.0%	36.8%
High school or less	13.2%	14.0%
Some college	41.0%	40.0%
College graduate	45.8%	46.0%
Industry work experience >= 10 years	41.4%	42.8%
Other industries	1.9%	2.0%
Construction	13.1%	11.3%
Manufacturing	5.3%	5.4%
Wholesale trade	3.0%	4.4%
Retail trade	10.9%	13.4%
Transportation and warehousing	3.8%	1.4%
Information	3.1%	4.1%
Finance, insurance and real estate	16.3%	11.7%
Professional services	14.4%	18.6%
Management	8.8%	9.3%
Health and educational services	4.0%	3.0%
Entertainment, accommodation and food services	4.2%	4.2%
Other services	11.1%	11.2%
Business Assets: Zero	24.0%	4.7%
Business Assets: $1-10,000	33.6%	34.1%
Business Assets: $10,000-25,000	11.6%	18.4%
Business Assets: $25,000-100,000	15.5%	25.2%
Business Assets: $100,000 or more	15.3%	17.7%
Patents	3.3%	1.1%
Copyrights	6.7%	8.2%
Trademarks	9.1%	8.6%
Any intellectural property	14.7%	13.9%
Hires employee next year	26.7%	21.9%
Sample size	1750	4169

Note: The sample consists of all non-employer observations over sample period, 2004 to 2011.

Appendix Table 4: LATE Estimates of Impact of Entrepreneurship Training on Hiring Employees for Non-Employer Business Owners at Baseline

	Treatment-Control (LATE/IV Estimates)		
	No Covars	Covariates	N
Dependent Variable	(1)	(2)	(3)
Has any employees by W1 survey date	0.0864	0.0989	302
	(0.1089)	(0.1108)	
Has any employees by W2 survey date	0.1257	0.2192	275
	(0.1868)	(0.1802)	
Has any employees by W3 survey date	0.2033	0.1956	225
	(0.2571)	(0.2988)	
Has any employees at W1 survey date	0.0864	0.0989	302
	(0.1089)	(0.1108)	
Has any employees at W2 survey date	-0.0104	0.0404	276
	(0.1580)	(0.1546)	
Has any employees at W3 survey date	-0.1545	-0.2514	228
	(0.1963)	(0.2267)	
Number of employees at W1	-0.3152	-0.3570	302
	(0.4814)	(0.5073)	
Number of employees at W2	-0.9478	-0.8013	276
	(0.7251)	(0.6797)	
Number of employees at W3	-0.5282	-0.7336	228
	(1.0317)	(1.3029)	

Notes: (1) The first-stage in the IV (LATE) model regresses receipt of entrepreneurship training on treatment. The second-stage regresses the listed outcome on predicted receipt of entrepreneurship training. (2) The wave 1, wave 2 and wave 3 surveys are conducted at 6, 18, and 60 months after time of application. (3) Covariates include program sites, female, race, immigrant, age, married, children, education level, household income, self-employed at application, health problems, worked in family business, bad credit history, unemployment compensation, employer provided health insurance, autonomy, and risk tolerance. (4) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Appendix Figure 1: Rates of Hiring First Employee and Going Out of Business for Non-Employer Startups
Kauffman Firm Survey (2004-2011)

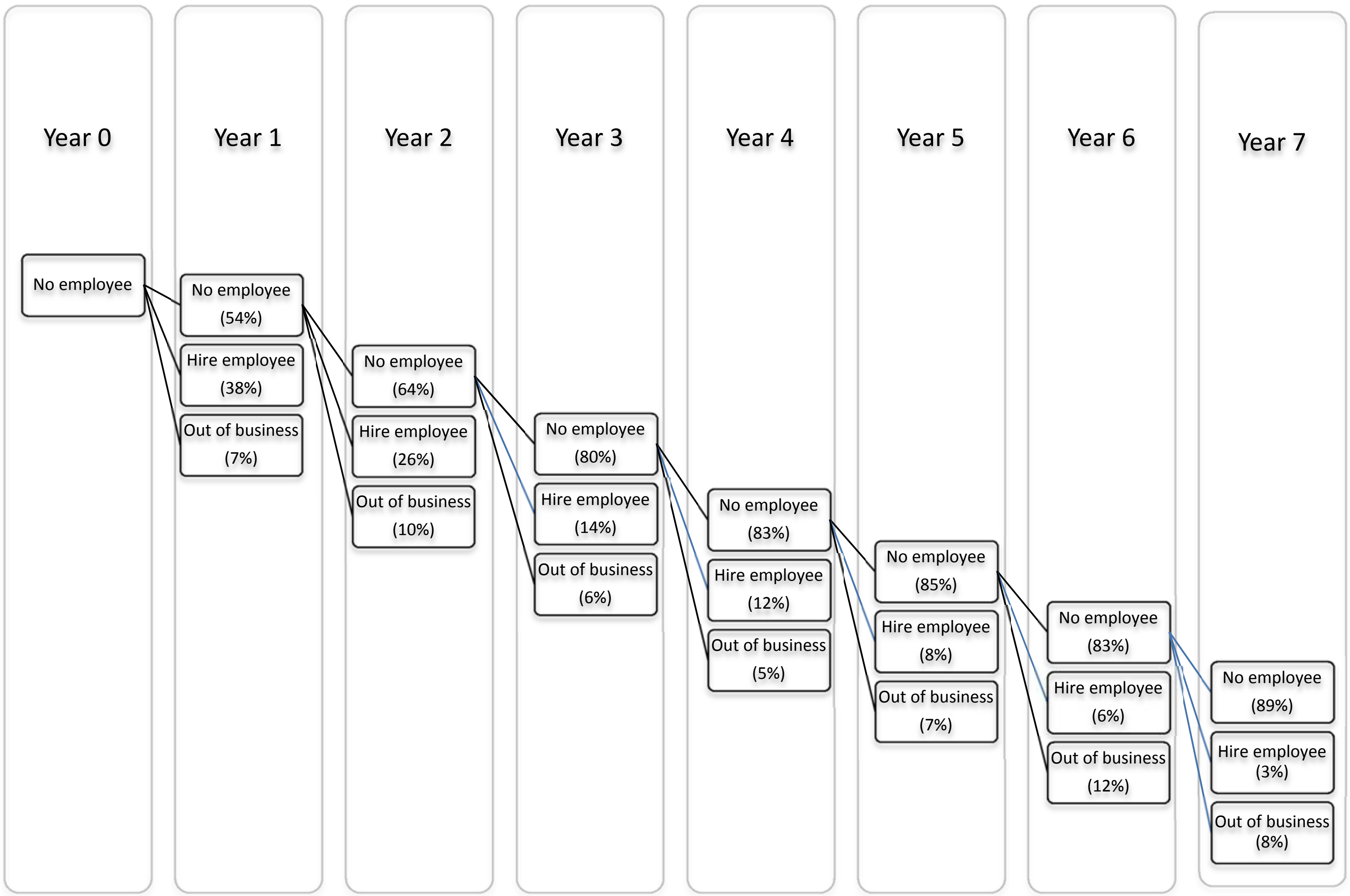

Table 1.A: Distribution across Years in which Non-Employer Startup Hired Its First Employee - All Non-Employers
Integrated Longitudinal Business Database (ILBD)

	Percent	Universe
Hired first employee at:		
1 year after startup	1.9%	84,500
2 years after startup	0.2%	10,200
3 years after startup	0.1%	4,900
4 years after startup	0.1%	2,900
5 years after startup	0.1%	2,500
6 years after startup	0.0%	1,500
7 years after startup	0.0%	1,200
Has not hired employee by end of study period	12.7%	556,200
Exit before hiring employee by end of study period	84.8%	3,704,800
Total number of non-employer startups:		4,368,700

Notes: (1) The data consists of the universe of non-employer startups in 1997. (2) Non-employer startups are defined as non-employers appearing in the non-employer data for the first time in at least three years.

Table 1.B: Distribution across Years in which Non-Employer Startup Hired Its First Employee - EIN Cases
Integrated Longitudinal Business Database (ILBD)

	Percent	Universe
Hired first employee at:		
1 year after startup	11.0%	63,900
2 years after startup	1.5%	8,800
3 years after startup	0.7%	4,100
4 years after startup	0.4%	2,400
5 years after startup	0.3%	1,800
6 years after startup	0.2%	1,200
7 years after startup	0.2%	1,000
Has not hired employee by end of study period	13.0%	75,700
Exit before hiring employee by end of study period	72.7%	422,300
Total number of non-employer startups:		581,200

Notes: (1) The data consists of the universe of non-employer startups in 1997. (2) Non-employer startups are defined as non-employers appearing in the non-employer data for the first time in at least three years.

Table 1.C: Distribution across Years in which Non-Employer Startup Hired Its First Employee - Incorporated Cases
Integrated Longitudinal Business Database (ILBD)

	Percent	Universe
Hired first employee at:		
1 year after startup	16.2%	52,700
2 years after startup	2.3%	7,500
3 years after startup	1.1%	3,500
4 years after startup	0.6%	2,100
5 years after startup	0.5%	1,500
6 years after startup	0.3%	1,000
7 years after startup	0.2%	800
Has not hired employee by end of study period	8.8%	28,600
Exit before hiring employee by end of study period	70.0%	227,800
Total number of non-employer startups:		325,500

Notes: (1) The data consists of the universe of non-employer startups in 1997. (2) Non-employer startups are defined as non-employers appearing in the non-employer data for the first time in at least three years.

Table 2.A: Distribution across Years in which Non-Employer Startup Hired Its First Employee
Kauffman Firm Survey (2004-2011)

	Percent	N
Hired first employee at:		
1 year after startup	36.6%	1590
2 years after startup	12.6%	1590
3 years after startup	4.0%	1590
4 years after startup	3.1%	1590
5 years after startup	1.4%	1590
6 years after startup	0.8%	1590
7 years after startup	0.4%	1590
Has not hired employee by end of study period	13.3%	1590
Out of business before hiring employee by end of study period	27.9%	1590

Notes: (1) The sample consists of businesses with no employees at startup in 2004. (2) The sample includes only businesses with non-missing information for all follow-up years.

Table 2B: Hiring Rates of First Employee by Year among Non-Employer Startups
Kauffman Firm Survey (2004-2011)

	Percent	N
Hire first employee by:		
1 year after startup	38.0%	2460
2 years after startup	51.0%	2214
3 years after startup	54.0%	1960
4 years after startup	57.2%	1810
5 years after startup	58.4%	1712
6 years after startup	58.5%	1626
7 years after startup	58.8%	1590

Note: The sample consists of businesses with no employees at startup in 2004. For each follow-up year only observations with non-missing information for all years up to that point are included.

Table 3: Owner Characteristics and Hiring Rates of First Employee among Non-Employer Startups
Kauffman Firm Survey (2004-2011)

	Hire First Employee by 1 Year after Startup		Hire First Employee by 2 Years after Startup		Hire First Employee by 7 Years after Startup	
Owner Characteristic	Percent	N	Percent	N	Percent	N
Total	38.0%	2460	51.0%	2214	58.8%	1590
White, non-Hispanic	36.3%	2010	48.9%	1823	57.9%	1326
African-American	38.8%	197	49.9%	169	58.5%	110
Asian-American	53.7%	81	68.9%	70	70.2%	51
Other race	51.3%	131	65.6%	114	67.0%	77
Hispanic	48.1%	118	64.5%	104	67.0%	68
Native born	37.4%	2220	50.3%	2005	58.8%	1452
Immigrant	44.8%	235	58.3%	204	58.6%	136
Male	41.0%	1762	54.5%	1592	62.2%	1140
Female	31.9%	696	43.9%	620	51.8%	449
High school or less	35.7%	309	48.9%	271	58.5%	182
Some college	36.7%	898	49.9%	796	55.1%	553
College graduate	40.0%	1243	52.7%	1137	62.2%	848
Industry work experience < 10 years	35.2%	1283	47.2%	1133	54.5%	813
Industry work experience >= 10 years	41.7%	1171	56.2%	1075	64.6%	773

Note: The sample consists of businesses with no employees at startup in 2004.

Table 4: Regressions for Probability of Hiring First Employee
Non-employer Startups - Kauffman Firm Survey (2004-2011)

Explanatory Variables	By 1 Year after Startup (1)		By 2 Years after Startup (2)		By 7 Years after Startup (3)	
African-American	0.00838		-0.00565		0.05406	
	(0.04258)		(0.04910)		(0.06387)	
Asian-American	0.17478	**	0.23409	***	0.17472	**
	(0.06897)		(0.07674)		(0.07932)	
Other race	0.12570	**	0.13483	**	0.15197	**
	(0.05140)		(0.05403)		(0.06377)	
Hispanic	0.07071		0.13196	**	0.12730	
	(0.05468)		(0.06050)		(0.07875)	
Immigrant	-0.01565		-0.02637		-0.06087	
	(0.04415)		(0.05123)		(0.06658)	
Female	-0.08755	***	-0.09266	***	-0.03513	
	(0.02474)		(0.02898)		(0.03788)	
Some college	0.01975		0.01476		-0.09452	*
	(0.03478)		(0.04234)		(0.05039)	
College graduate	0.04388		0.02914		-0.08744	*
	(0.03527)		(0.04271)		(0.04743)	
Industry work exp. > 10 years	0.03302		0.05531	**	0.02439	
	(0.02298)		(0.02609)		(0.03433)	
Other industry	-0.01589		-0.08660		-0.24204	
	(0.09890)		(0.10919)		(0.16904)	
Construction	0.07575		0.04544		0.09997	
	(0.04964)		(0.05699)		(0.07534)	
Manufacturing	0.14575	***	0.12237	*	0.09981	
	(0.05570)		(0.06538)		(0.08850)	
Wholesale trade	0.25716	***	0.17615	**	0.21710	***
	(0.06048)		(0.06953)		(0.08295)	
Retail trade	0.08518	*	0.05171		0.07725	
	(0.04684)		(0.05404)		(0.07745)	
Transportation and	0.12147		0.19142	**	0.21907	**
warehousing	(0.07555)		(0.08966)		(0.09122)	
Information	-0.03328		-0.01662		-0.06866	
	(0.06582)		(0.07588)		(0.10955)	
Finance, insurance and real	-0.05926		-0.08031		-0.04966	
estate	(0.04934)		(0.05928)		(0.08550)	
Professional services	0.12143	***	0.06974		0.12723	*
	(0.04231)		(0.04889)		(0.06607)	
Management	0.07932		0.12508	**	0.14899	*
	(0.04891)		(0.05734)		(0.07638)	
Health and educational services	0.08719		0.05560		0.15946	
	(0.07186)		(0.08357)		(0.11404)	
Entertainment, accommodation	0.01381		0.01163		-0.04673	
and food services	(0.06352)		(0.08011)		(0.11191)	
	0.37991		0.56187		0.73760	
Sample size	2419		1982		931	

Notes: (1) The sample consists of businesses with no employees at startup in 2004. (2) Regional controls are included in all specifications. (3) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 5: Regressions for Probability of Hiring First Employee including Legal Form of Organization
Non-employer Startups - Kauffman Firm Survey (2004-2011)

Explanatory Variables	By 1 Year after Startup (1)		By 2 Years after Startup (2)		By 7 Years after Startup (3)	
African-American	0.01034		-0.00366		0.06132	
	(0.04274)		(0.04959)		(0.06620)	
Asian-American	0.17392	**	0.24039	***	0.17309	**
	(0.06891)		(0.07826)		(0.08546)	
Other race	0.12539	**	0.13259	**	0.14550	**
	(0.05111)		(0.05337)		(0.06643)	
Hispanic	0.07476		0.13187	**	0.12716	
	(0.05448)		(0.06014)		(0.08069)	
Immigrant	-0.02032		-0.02839		-0.06111	
	(0.04395)		(0.05112)		(0.07029)	
Female	-0.08134	***	-0.08636	***	-0.02430	
	(0.02475)		(0.02905)		(0.03783)	
Some college	0.01558		0.00931		-0.10647	**
	(0.03457)		(0.04232)		(0.05096)	
College graduate	0.03296		0.01626		-0.11064	**
	(0.03528)		(0.04299)		(0.04882)	
Industry work exp. > 10 years	0.03072		0.05432	**	0.02239	
	(0.02293)		(0.02607)		(0.03439)	
Other industry	-0.03129		-0.10504		-0.26844	
	(0.09977)		(0.10849)		(0.16663)	
Construction	0.06745		0.03233		0.08164	
	(0.04986)		(0.05691)		(0.07519)	
Manufacturing	0.13623	**	0.11074	*	0.08227	
	(0.05522)		(0.06557)		(0.08912)	
Wholesale trade	0.24504	***	0.15788	**	0.18410	**
	(0.06022)		(0.06968)		(0.08441)	
Retail trade	0.07800	*	0.03926		0.06719	
	(0.04683)		(0.05429)		(0.07661)	
Transportation and warehousing	0.10656		0.17467	**	0.19072	**
	(0.07640)		(0.08910)		(0.09246)	
Information	-0.03497		-0.02492		-0.05656	
	(0.06661)		(0.07559)		(0.10771)	
Finance, insurance and real estate	-0.08099		-0.09314		-0.07188	
	(0.05049)		(0.05941)		(0.08645)	
Professional services	0.11198	***	0.05687		0.10927	*
	(0.04241)		(0.04913)		(0.06635)	
Management	0.07356		0.11384	**	0.13076	*
	(0.04866)		(0.05771)		(0.07668)	
Health and educational services	0.08124		0.03695		0.14838	
	(0.07128)		(0.08375)		(0.11582)	
Entertainment, accommodation and food services	0.00350		0.00017		-0.04575	
	(0.06360)		(0.08032)		(0.11238)	
Incorporated	0.06045	**	0.04264		0.08700	**
	(0.02612)		(0.02934)		(0.03799)	
Partnership	0.04194		-0.08990		-0.05928	
	(0.05408)		(0.06198)		(0.10680)	
Mean of Dep. Variable	0.37991		0.56187		0.73760	
Sample size	2419		1982		931	

Notes: (1) The sample consists of businesses with no employees at startup in 2004. (2) Regional controls are included in all specifications. (3) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 6: Annual Rates of Hiring First Employee
Non-Employer Panel Data - Kauffman Firm Survey (2004-2011)

	Hire First Employee	
Milestone	Percent	N
All Non-Employer Observations	23.4%	6092
Total Revenues (Annual)		
Zero	26.7%	1750
$1-10,000	18.6%	1313
$10,000-25,000	19.8%	710
$25,000-100,000	21.4%	1369
$100,000 or more	30.4%	777
Total Business Assets		
Zero	22.0%	667
$1-10,000	19.7%	2130
$10,000-25,000	24.6%	1013
$25,000-100,000	28.2%	1342
$100,000 or more	24.2%	920
Patents		
No	23.3%	5867
Yes	31.9%	168
Copyrights		
No	23.2%	5447
Yes	28.1%	535
Trademarks		
No	22.4%	5382
Yes	35.6%	586
Any intellectual property		
No	22.4%	4951
Yes	31.2%	940

Note: The sample consists of all non-employer observations over sample period, 2004 to 2011.

Table 7: Regressions for Annual Probability of Hiring First Employee
Non-Employer Panel Data - Kauffman Firm Survey (2004-2011)

Explanatory Variables	In Following Year (1)		In Following Year (2)		In Following Year (3)		In Following Year (4)	
African-American	0.01613		0.00594		-0.00150		0.02098	
	(0.03221)		(0.03209)		(0.03203)		(0.03240)	
Asian-American	0.15645	**	0.18576	***	0.18753	***	0.18813	***
	(0.06803)		(0.06900)		(0.06930)		(0.06850)	
Other race	0.13127	***	0.11198	**	0.11485	**	0.11975	***
	(0.04513)		(0.04809)		(0.04732)		(0.04635)	
Hispanic	0.11114	**	0.11271	**	0.11263	**	0.11206	**
	(0.05336)		(0.05503)		(0.05445)		(0.05411)	
Immigrant	0.01809		0.01743		0.01828		0.01720	
	(0.03663)		(0.03877)		(0.03855)		(0.03756)	
Female	-0.05342	***	-0.04123	**	-0.04524	***	-0.04228	**
	(0.01666)		(0.01704)		(0.01705)		(0.01688)	
Some college	-0.01868		-0.01937		-0.02212		-0.02015	
	(0.02579)		(0.02582)		(0.02595)		(0.02579)	
College graduate	0.00106		-0.00504		-0.00745		-0.00045	
	(0.02580)		(0.02597)		(0.02617)		(0.02596)	
Industry work exp. > 10 years	0.03943	**	0.03625	**	0.03511	**	0.03836	**
	(0.01634)		(0.01665)		(0.01668)		(0.01652)	
Revenues: $1-$10,000			-0.06380	***	-0.06557	***		
			(0.02028)		(0.02002)			
Revenues: $10,001-$25,000			-0.07024	***	-0.06052	***		
			(0.02321)		(0.02308)			
Revenues: $25,001-$100,000			-0.06149	***	-0.04157	**		
			(0.01969)		(0.01929)			
Revenues: $100,000 or more			-0.00204		0.02897			
			(0.02860)		(0.02765)			
Business assets: $1-$10,000			0.02041				-0.00814	
			(0.02323)				(0.02279)	
Business assets: $10,001-$25,000			0.06255	**			0.03479	
			(0.02760)				(0.02700)	
Business assets: $25,001-$100,000			0.08812	***			0.06469	**
			(0.02681)				(0.02603)	
Business assets: $100,000 or more			0.07367	**			0.05923	**
			(0.02903)				(0.02818)	
Intellectual property			0.07379	***	0.07598	***	0.07995	***
			(0.02321)		(0.02321)		(0.02333)	
Mean of Dep. Variable	0.23364		0.23531		0.23526		0.23538	
Sample size	5793		5452		5455		5593	

Notes: (1) The sample consists of all non-employer observations over sample period, 2004 to 2011. The unit observation is a business-year. (2) Industry and regional controls are included in all specifications. (3) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 8: Regressions for Annual Probability of Hiring First Employee including only Businesses with Revenues
Non-Employer Panel Data - Kauffman Firm Survey (2004-2011)

Explanatory Variables	In Following Year (1)		In Following Year (2)		In Following Year (3)		In Following Year (4)	
African-American	-0.01531		-0.00914		-0.01404		-0.01261	
	(0.04044)		(0.04102)		(0.04053)		(0.04100)	
Asian-American	0.11369		0.15396	*	0.15597	*	0.14705	*
	(0.08564)		(0.08592)		(0.08580)		(0.08621)	
Other race	0.18526	***	0.16512	**	0.17400	***	0.16612	**
	(0.06469)		(0.06775)		(0.06640)		(0.06668)	
Hispanic	0.10238		0.11102		0.10927		0.10679	
	(0.07062)		(0.07244)		(0.07141)		(0.07167)	
Immigrant	0.03152		0.02764		0.02850		0.02991	
	(0.04573)		(0.04796)		(0.04809)		(0.04655)	
Female	-0.06438	***	-0.05118	***	-0.05417	***	-0.05362	***
	(0.01902)		(0.01932)		(0.01944)		(0.01927)	
Some college	0.01075		0.01347		0.00966		0.01468	
	(0.02860)		(0.02840)		(0.02860)		(0.02854)	
College graduate	0.01511		0.01293		0.00918		0.01567	
	(0.02892)		(0.02879)		(0.02913)		(0.02894)	
Industry work exp. > 10 years	0.04201	**	0.03649	*	0.03503	*	0.03934	**
	(0.01849)		(0.01879)		(0.01882)		(0.01868)	
Revenues: $1-$10,000								
Revenues: $10,001-$25,000			-0.01267		0.00080			
			(0.02307)		(0.02291)			
Revenues: $25,001-$100,000			-0.00588		0.01882			
			(0.02222)		(0.02102)			
Revenues: $100,000 or more			0.05509	*	0.09175	***		
			(0.03084)		(0.02883)			
Business assets: $1-$10,000			0.07753	***			0.07404	***
			(0.02664)				(0.02680)	
Business assets: $10,001-$25,000			0.11764	***			0.11617	***
			(0.03108)				(0.03095)	
Business assets: $25,001-$100,000			0.14693	***			0.15522	***
			(0.03040)				(0.03020)	
Business assets: $100,000 or more			0.13240	***			0.14923	***
			(0.03440)				(0.03370)	
Intellectual property			0.05170	**	0.05662	**	0.05426	**
			(0.02577)		(0.02590)		(0.02573)	
Mean of Dep. Variable	0.21876		0.22045		0.22042		0.22045	
Sample size	3975		3841		3842		3841	

Notes: (1) The sample consists of all non-employer observations with non-zero revenues over sample period, 2004 to 2011. The unit observation is a business-year. (2) Industry and regional controls are included in all specifications. (3) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 9: Regressions for Annual Probability of Hiring First Employee in Services Industries
Non-Employer Panel Data - Kauffman Firm Survey (2004-2011)

Explanatory Variables	In Following Year (1)		In Following Year (2)		In Following Year (3)		In Following Year (4)	
African-American	0.03894		0.02898		0.02396		0.03741	
	(0.03626)		(0.03571)		(0.03557)		(0.03616)	
Asian-American	0.14699	*	0.17646	**	0.17721	**	0.17809	**
	(0.08018)		(0.07971)		(0.08102)		(0.07991)	
Other race	0.07472		0.05551		0.05774		0.06479	
	(0.04577)		(0.04954)		(0.04868)		(0.04682)	
Hispanic	0.16409	***	0.17559	***	0.17230	***	0.16894	***
	(0.05809)		(0.06069)		(0.06017)		(0.05917)	
Immigrant	0.00959		0.01106		0.01203		0.00309	
	(0.04238)		(0.04526)		(0.04542)		(0.04319)	
Female	-0.06331	***	-0.05483	***	-0.05621	***	-0.05773	***
	(0.01890)		(0.01918)		(0.01930)		(0.01906)	
Some college	0.00085		-0.00500		-0.00987		-0.00010	
	(0.03252)		(0.03339)		(0.03360)		(0.03275)	
College graduate	-0.00602		-0.01526		-0.01974		-0.00837	
	(0.03199)		(0.03296)		(0.03325)		(0.03234)	
Industry work exp. > 10 years	0.03300	*	0.02418		0.02488		0.02854	
	(0.01880)		(0.01911)		(0.01916)		(0.01900)	
Revenues: $1-$10,000			-0.03554		-0.03275			
			(0.02421)		(0.02406)			
Revenues: $10,001-$25,000			-0.01943		-0.00957			
			(0.02797)		(0.02783)			
Revenues: $25,001-$100,000			-0.05796	***	-0.04213	*		
			(0.02247)		(0.02206)			
Revenues: $100,000 or more			0.04599		0.05773	*		
			(0.03468)		(0.03438)			
Business assets: $1-$10,000			0.02405				0.01376	
			(0.02680)				(0.02571)	
Business assets: $10,001-$25,000			0.09125	***			0.07803	**
			(0.03235)				(0.03144)	
Business assets: $25,001-$100,000			0.05284	*			0.04867	
			(0.03121)				(0.02992)	
Business assets: $100,000 or more			0.03040				0.03725	
			(0.03268)				(0.03202)	
Intellectual property			0.05320	**	0.05464	**	0.05574	**
			(0.02617)		(0.02620)		(0.02612)	
Mean of Dep. Variable	0.21624		0.21826		0.21818		0.21736	
Sample size	3716		3497		3499		3587	

Notes: (1) The sample consists of all non-employer observations in the services industries over sample period, 2004 to 2011. The unit observation is a business-year. (2) Industry and regional controls are included in all specifications. (3) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 10: Regressions for Annual Probability of Hiring First Employee in Construction, Trade, Manufacturing, and Other Industries
Non-Employer Panel Data - Kauffman Firm Survey (2004-2011)

Explanatory Variables	In Following Year (1)		In Following Year (2)		In Following Year (3)		In Following Year (4)	
African-American	-0.03484		-0.04780		-0.05602		-0.02316	
	(0.05637)		(0.05927)		(0.05912)		(0.05934)	
Asian-American	0.19793	*	0.25723	***	0.25749	**	0.24691	**
	(0.11080)		(0.09885)		(0.10667)		(0.10188)	
Other race	0.23075	***	0.19378	**	0.21335	**	0.20403	**
	(0.08747)		(0.09173)		(0.08937)		(0.08994)	
Hispanic	0.03478		0.03300		0.03479		0.03585	
	(0.08394)		(0.07932)		(0.08121)		(0.08065)	
Immigrant	0.02244		0.01363		0.01496		0.02534	
	(0.06389)		(0.06578)		(0.06441)		(0.06662)	
Female	-0.02926		0.00097		-0.01004		-0.00195	
	(0.03135)		(0.03182)		(0.03204)		(0.03122)	
Some college	-0.03824		-0.02776		-0.03390		-0.03336	
	(0.03881)		(0.03749)		(0.03778)		(0.03774)	
College graduate	0.03947		0.03275		0.03417		0.03898	
	(0.04166)		(0.04101)		(0.04134)		(0.04129)	
Industry work exp. > 10 years	0.06054	**	0.07212	**	0.06709	**	0.07133	**
	(0.02998)		(0.03050)		(0.03023)		(0.03019)	
Revenues: $1-$10,000			-0.11233	***	-0.12286	***		
			(0.03512)		(0.03478)			
Revenues: $10,001-$25,000			-0.16260	***	-0.16098	***		
			(0.03960)		(0.03915)			
Revenues: $25,001-$100,000			-0.06566	*	-0.03727			
			(0.03636)		(0.03526)			
Revenues: $100,000 or more			-0.06664		-0.00680			
			(0.04792)		(0.04435)			
Business assets: $1-$10,000			0.00669				-0.05468	
			(0.04470)				(0.04473)	
Business assets: $10,001-$25,000			0.02643				-0.03355	
			(0.05019)				(0.04936)	
Business assets: $25,001-$100,000			0.12735	**			0.06840	
			(0.04961)				(0.04809)	
Business assets: $100,000 or more			0.13181	**			0.07935	
			(0.05703)				(0.05426)	
Intellectual property			0.09773	**	0.10088	**	0.11985	***
			(0.04302)		(0.04369)		(0.04356)	
Mean of Dep. Variable	0.26185		0.26283		0.26282		0.26441	
Sample size	2077		1955		1956		2006	

Notes: (1) The sample consists of all non-employer observations in the construction, manufacturing, trade, and other industries over sample period, 2004 to 2011. The unit observation is a business-year. (2) Industry and regional controls are included in all specifications. (3) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 11: Treatment/Control Comparison of Baseline Characteristics for GATE Experiment

	Treatment Group	Control Group	P-Value for Treat-Control
	(1)	(2)	(3)
Philadelphia	19.0%	16.0%	0.47
Pittsburgh	10.3%	14.8%	0.22
Minneapolis-St. Paul	52.3%	49.1%	0.56
Duluth	3.5%	5.3%	0.40
Maine	14.9%	14.8%	0.97
Female	46.0%	45.0%	0.85
Black	25.3%	23.8%	0.75
Latino	8.6%	4.8%	0.15
Asian	2.9%	4.2%	0.52
Other	6.9%	8.3%	0.62
Not U.S. born	9.2%	9.5%	0.93
Age	44.19	43.70	0.66
Married	46.6%	55.1%	0.12
Has children	46.0%	47.3%	0.80
Highest grade completed	15.07	15.21	0.56
HH Income $25,000-49,999	28.3%	29.2%	0.86
HH Income $50,000-74,999	19.7%	20.8%	0.79
HH Income $75,000-99,999	5.2%	5.4%	0.95
HH Income $100,000+	5.2%	6.6%	0.60
Has a health problem	7.5%	5.9%	0.57
Has relatives or friends who have been previously S.E.	75.3%	74.6%	0.88
Ever worked for relatives or friends who are S.E.	30.5%	26.6%	0.43
Has a bad credit history	41.4%	37.3%	0.44
Currently receiving UI benefits	31.6%	25.6%	0.22
Sample Size	174	169	

Notes: (1) All reported characteristics are measured at time of application, prior to random assignment. (2) Sample includes only non-employer business owners at time of application.

Table 12: Treatment and Control Groups Receipt of Entrepreneurship Training

	R.A. to Wave 1 (6 month period)		Wave 1 to Wave 2 (12 month period)		Year Prior to Wave 3 (12 month period)		Cumulative to Wave 2		Cumulative to Wave 3	
	Percent Receiving	Mean Hours	Percent Receiving	Mean Hours	Percent Receiving	Mean Hours	Percent Receiving	Mean Hours	Percent Receiving	Mean Hours
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment group										
Any entrepreneurship training	86.0%	18.0	50.0%	9.7	31.7%	6.8	86.4%	27.8	88.7%	34.5
Attended classes, workshops or seminars	72.0%	15.9	45.8%	8.9	28.5%	5.9	74.1%	24.8	77.0%	30.7
Received one-on-one counseling or technical	57.3%	2.1	18.1%	1.1	17.1%	0.7	58.8%	3.2	63.7%	3.9
Control group										
Any entrepreneurship training	53.7%	9.1	47.8%	8.7	40.2%	7.9	57.3%	17.8	65.4%	25.7
Attended classes, workshops or seminars	46.3%	8.2	44.0%	7.3	37.4%	7.3	50.6%	15.5	58.7%	22.8
Received one-on-one counseling or technical	22.4%	0.9	20.1%	1.5	11.2%	0.6	27.9%	2.5	34.4%	3.1

Note: The wave 1, wave 2 and wave 3 surveys are conducted at 6, 18, and 60 months after time of application.

Table 13: Self-Reported Amount that Entrepreneurship Training Helped Recipients in Various Ways

	Very Useful	Somewhat Useful	Not Very Useful	Not at All Useful
How would you rate the overall usefulness of the services you have received?				
Treatment group	48.6%	31.3%	12.5%	7.6%
Control group	35.6%	45.5%	6.9%	11.9%

	Treatment Group			Control Group		
GATE Services	A Lot	Somewhat	Not at All	A Lot	Somewhat	Not at All
Helped with applying for loans	9.4%	23.2%	67.4%	0.0%	11.0%	89.0%
Helped with deciding whether to pursue self. em	37.1%	20.3%	42.7%	23.3%	24.3%	52.4%
Helped with refining the business idea	32.9%	37.1%	30.1%	25.2%	33.0%	41.7%
Helped with credit issues	18.2%	27.3%	54.5%	6.9%	18.8%	74.3%
Helped with developing a marketing strategy	34.3%	35.0%	30.8%	22.3%	31.1%	46.6%
Helped with legal issues	13.3%	32.9%	53.8%	10.7%	24.3%	65.0%
Helped with accounting issues	22.9%	34.0%	43.1%	8.7%	31.1%	60.2%
Helped with hiring and dealing with employees	9.2%	18.3%	72.5%	5.8%	17.5%	76.7%
Helped with networking	31.3%	32.6%	36.1%	23.3%	29.1%	47.6%
Helped with using computers and technology	8.3%	29.2%	62.5%	5.8%	23.3%	70.9%
Helped with dealing with clients	19.4%	36.1%	44.4%	13.6%	31.1%	55.3%
Helped with providing psychological support	19.0%	28.2%	52.8%	15.7%	21.6%	62.7%

Notes: (1) Sample includes treatment and control group participants who received any entrepreneurship training by wave 1 follow-up survey (6 months). (2) Evaluation of services was asked at W1.

Table 14: Impact of Entrepreneurship Training on Hiring Employees for Non-Employer Business Owners at Baseline

	Treatment-Control ITT Estimates		
	No Covars	Covariates	N
Dependent Variable	(1)	(2)	(3)
Has any employees by W1 survey date	0.0277	0.0319	302
	(0.0349)	(0.0357)	
Has any employees by W2 survey date	0.0303	0.0532	275
	(0.0450)	(0.0438)	
Has any employees by W3 survey date	0.0418	0.0349	225
	(0.0529)	(0.0533)	
Has any employees at W1 survey date	0.0277	0.0319	302
	(0.0349)	(0.0357)	
Has any employees at W2 survey date	-0.0025	0.0098	276
	(0.0382)	(0.0375)	
Has any employees at W3 survey date	-0.0325	-0.0459	228
	(0.0413)	(0.0413)	
Number of employees at W1	-0.1011	-0.1152	302
	(0.1544)	(0.1637)	
Number of employees at W2	-0.2292	-0.1944	276
	(0.1753)	(0.1649)	
Number of employees at W3	-0.1110	-0.1338	228
	(0.2169)	(0.2376)	

Notes: (1) Intent-to-Treat (ITT) estimates are reported for the listed outcome regressed on entrepreneurship training treatment. (2) The wave 1, wave 2 and wave 3 surveys are conducted at 6, 18, and 60 months after time of application. (3) Covariates include program sites, female, race, immigrant, age, married, children, education level, household income, self-employed at application, health problems, worked in family business, bad credit history, unemployment compensation, employer provided health insurance, autonomy, and risk tolerance. (4) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 15: Impact of Entrepreneurship Training on Business Ownership and Sales for Non-Employer Business Owners at Baseline

	Treatment-Control ITT Estimates			
	No Covars		Covariates	N
Dependent Variable	(1)		(2)	(3)
Business owner at W1 survey date	-0.0296		-0.0052	302
	(0.0454)		(0.0464)	
Business owner at W2 survey date	-0.0017		0.0046	278
	(0.0539)		(0.0551)	
Business owner at W3 survey date	0.0555		0.0213	230
	(0.0627)		(0.0666)	
Monthly business sales at W1 survey date (000s)	-0.5808		-0.5062	252
	(0.5336)		(0.5281)	
Monthly business sales at W2 survey date (000s)	-1.3105	*	-1.1815	235
	(0.7545)		(0.7225)	
Monthly business sales at W3 survey date (000s)	-0.8671		-0.8182	214
	(2.9767)		(2.8160)	

Notes: (1) Intent-to-Treat (ITT) estimates are reported for the listed outcome regressed on entrepreneurship training treatment. (2) The wave 1, wave 2 and wave 3 surveys are conducted at 6, 18, and 60 months after time of application. (3) Covariates include program sites, female, race, immigrant, age, married, children, education level, household income, self-employed at application, health problems, worked in family business, bad credit history, unemployment compensation, employer provided health insurance, autonomy, and risk tolerance. (4) *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.