

Job Creation and Survival among Entrepreneurs: Evidence from the Universe of U.S. Startups

Robert W. Fairlie - University of California, Santa Cruz and NBER
rfairlie@ucsc.edu

Javier Miranda - U.S. Census Bureau
javier.miranda@census.gov

Nikolas Zolas - U.S. Census Bureau
nikolas.j.zolas@census.gov

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Abstract

Entrepreneurship is promoted around the world by governments and policymakers, but surprisingly, we do not know the answers to three fundamental questions important for basic welfare calculations: i) How many jobs does an entrepreneur create?, ii) Do these jobs disappear quickly?, and iii) How many entrepreneurs survive each year after startup? We provide the first definitive answers to these three questions using a new compilation of administrative data that captures the universe of U.S. startups. The average entrepreneur creates 0.56 jobs at startup (using the broadest definition possible). These jobs do not disappear quickly as the average startup employs 0.53 workers five years later. In total, the average annual cohort of 5.4 million startups in the United States creates 3.0 million jobs in the startup year and employs 2.9 million workers five years later. Without these jobs, net job creation by all other businesses would be negative. We also find extremely low survival rates – only 41 percent of startups survive two years and only 20 percent survive five years, with no industries being immune. Exploring the rich heterogeneity in the early-stage dynamics of startups, we find that the negative influence from the high exit rates on job creation is mostly offset by rapid job growth over time among surviving startups. This rapid growth in job creation among survivors is not driven by a few extremely successful startups, but instead is driven by a continuous upward shift in the employment size distribution. Exploring heterogeneity across startup types, we find that non-employer startups make sizeable contributions to employment several years after startup (22 percent of jobs seven years later). Instead of excluding all non-employer startups, we exclude sole proprietor non-employer startups to create a more restrictive definition of entrepreneurship. Using this upper bound measure, we find a job creation rate of 2.0 jobs per startup and a survival rate of 30 percent five years later. These findings have important policy, theoretical and welfare implications.

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I. Introduction

Many policymakers and organizations around the world call upon entrepreneurs to create new jobs. Federal, state and local governments spend billions of dollars each year on incubators, training programs, loan programs, tax breaks, and investor incentives to encourage business creation with one of the primary goals being to create jobs.¹ Expenditures are generally made, however, without measurement of the benefits in terms of the number of businesses, jobs or total payroll created relative to the costs of these programs.² Surprisingly, relevant to any benefit to cost calculation, we do not know the answers to the fundamental questions of how many jobs does the average entrepreneur create or what percentage of entrepreneurs survive one, two, or more years later?³ But, in spite of the perception of high failure rates and uncertainty over job creation, the popularity of public policies to foster entrepreneurs continues to grow around the world (OECD 2017).

Measuring job creation and survival among entrepreneurs is also important for better understanding the fundamental nature of entrepreneurship. Is entrepreneurship about creating innovative products, services and jobs (i.e. Schumpeterian entrepreneurship), or is it becoming increasingly about job independence (i.e. being one's own boss), contract/consulting work, schedule flexibility, or being part of the gig economy (Hamilton 2000; Hurst and Pugsley 2011; Levine and Rubinstein 2016; Katz and Krueger 2017)? In other words, is entrepreneurship about

¹ The U.S. Small Business Administration, for example, administers several programs to support small businesses, including loan guaranty, training, federal contracting, and other programs.

² The evidence on the effectiveness of programs to spur entrepreneurship is mixed. For a few recent examples, see Brown and Earle (2016) on SBA lending programs, Chrisman (2016) on Small Business Development Centers (SBDCs), Lerner (1999) on the SBIR program, Fairlie, Karlan and Zinman (2015) on entrepreneurship training, Huber et al. (2014) on entrepreneurship education, Chatterji, Chay and Fairlie (2014) on contracting programs, and Mathematica (2017) on SEA programs.

³ Recently, the U.S. Government Accounting Office (GAO) recommended that the SBA use job creation and other outcome-based measures to evaluate the effectiveness of its programs (CRS 2017). Also, SBDCs, which are partly funded by SBA, measure job creation resulting from their training and assistance centers around the country from surveys of participants (Chrisman 2016).

creating *jobs* or creating *a job*? Is it about creating a long-term job or just a temporary job? And, finally, is it about taking risks (Knight 1921; Kihlstrom and Laffont 1979) or diversifying risk (i.e. through multiple job activities)?

This paper uses new administrative data on the universe of business startups in the United States to answer three fundamental questions about how we think about entrepreneurship from a policy, economic welfare, and theoretical perspective. Using the universe of startups, we provide the first definitive answers to: i) How many jobs are created by the average entrepreneur?, ii) Do these jobs last over time?, and iii) How many entrepreneurs survive each year after startup?⁴ In addition to providing answers to these fundamental questions, we test several proposed explanations for the underlying causes of patterns in entrepreneurial job creation and survival.

To track job creation and survival over time by every business startup in the U.S. economy, we link the universe of non-employer firms to the universe of employer firms in the Longitudinal Business Database (LBD). To create the necessary links between non-employer and employer definitions, we update and expand the Integrated Longitudinal Business Database (iLBD).⁵ In the process, we create a new compilation of existing administrative data that covers the universe of startups over several follow-up years.

To measure entrepreneurial job creation and survival rates, we start by including all startups and then consider alternative definitions. The classic studies of entrepreneurship, such as Knight (1921), Schumpeter (1934) and more recently Kihlstrom and Laffont (1979), Jovanovic

⁴ There is no universally agreed upon or official definition of “entrepreneurs” in government data or research (Decker et al. 2015; Parker 2009). The U.S. Bureau of Labor Statistics (BLS) publishes statistics on “entrepreneurs” that are defined as new employer establishments. We follow this approach of defining entrepreneurship as new businesses or business startups.

⁵ A beta version of the iLBD was first introduced by Davis et al (2007) to study transitions between non-employer and employer business units for a subset of industries in 1992 and 1994. Subsequently, Fairlie and Miranda (2016) created another beta version with one non-employer startup cohort from 1997 to examine transitions to employer businesses.

(1982) and Evans and Jovanovic (1989), that have helped establish entrepreneurship as an independent field in economics do not limit the definition of entrepreneurship by employer, incorporation or any other status. The federal government recently started publishing aggregate data on the “number of firm startups” (U.S. Census Bureau 2017) and “entrepreneurship in the U.S. economy” (U.S. Bureau of Labor Statistics 2017), but these data measure only new *employer* businesses or establishments.⁶ This is important because estimates of job creation per *employer* startup will greatly overestimate job creation per *any* startup. Non-employer firms comprise the majority of both startups and total firms in the United States. Also, employer firms will be misclassified as new businesses if they actually started several years earlier with no employees, and jobs eventually created by non-employer startups will be credited to the wrong startup cohort. The inclusion of non-employer startups is also important for correctly measuring exit rates over time because many non-employer firms exit before ever hiring an employee. Currently, the BLS reports survival rates only for new employer establishments. In general, ignoring the non-employer history of firms is likely to miss important early entrepreneurial dynamics that are crucial to understanding the relationships between entrepreneurship, job creation, and survival.

The analysis of the new administrative dataset on the universe of U.S. startups provides several findings that shed light on fundamental, and surprisingly unanswered, questions regarding the job creation potential and survival of entrepreneurs. Using the broadest definition possible, we find that the average entrepreneur creates 0.56 jobs at startup, and employs 0.53

⁶ The previous research on job creation among businesses, however, focuses almost exclusively on employer firms (e.g. Haltiwanger, Jarmin and Miranda 2013; Kulick, Haltiwanger, Jarmin; Miranda 2016; Glaeser, Kerr and Ponzetto 2010; Glaeser, Kerr and Kerr 2015; Tracy 2011; Decker et al. 2014; Garcia-Macia, Hsieh, and Klenow 2016). Data on non-employer startups are more difficult to find and are not reported by age of business over time. Among OECD countries, the United States is one of the few countries that does not report non-employer business creation rates (see OECD 2017, Figure 4.1 for example).

workers five years later and 0.50 workers seven years later.⁷ The average annual cohort of 5.4 million startups in the United States creates a total of 3.0 million jobs in the startup year and employs 2.9 million workers five years later. Without these jobs created by startups, net job creation would be negative and total more than 1 million job losses per year. We also find that survival rates are extremely low among the universe of startups with a large shake out occurring in the years immediately after startup. After one year, only 59 percent of startups survive and after two years only 41 percent survive. The decline in survival rates starts to taper off and after 5 years, the survival rate is 21 percent. Surprisingly, survival rates are remarkably consistent across industries, differing from job creation, which varies substantially across industries.

We also test several competing hypotheses regarding the underlying causes of job creation dynamics. Exploring the rich heterogeneity in job creation dynamics across the universe of startups, we find that rapid job growth over time among surviving startups mostly offsets the negative influence from extremely high exit rates. Surviving startups hire an average of 2.5 employees five years after startup and 3.3 employees seven years after startup (compared with hiring 0.56 employees at startup). We also find that increasing average employment per surviving startup is not driven by a few extremely successful firms, but is instead driven by a continuous upward shift in the employment size distribution.

When we turn to investigating heterogeneity based on business type at startup we find that non-employer startups make substantial contributions to job creation: an average of 594,000 jobs seven years after startup representing one-fifth of the total 2.7 million jobs created by all startups. We also examine whether the inclusive definition of entrepreneurship explains why job

⁷ We focus here on net employment levels over time per startup. The data do not provide information on gross flows during the year or whether employees were previous unemployed, out of the labor force, or working for another business.

creation is low and survival rates are low. Because of concerns over including all non-employer business entities, we also experiment with more restrictive definitions. Using a more restrictive definition of entrepreneurship that includes employer, incorporated, partnership and S-corporation startups, but excludes sole proprietorships, we find that the average entrepreneur creates 2.3 jobs at startup and 2.0 jobs five years later. Although job creation is higher among this select group of startups, survival rates remain extremely low, with 52 percent surviving after 2 years and 30 percent surviving after 5 years. We view these levels of job creation per entrepreneur and survival rates as upper bounds. These findings paint a picture of the U.S. entrepreneur as one who creates few jobs and experiences high exit rates, but when surviving grows steadily.

Our paper is related to several influential studies on job creation among small businesses. These studies focus on identifying the share of jobs created by small or young businesses relative to large or older businesses. Starting with the seminal study by Birch (1979) showing that small businesses are the principal driver of job creation in the U.S. economy, there has been considerable interest in job creation among entrepreneurs. Recent evidence indicates that young and high-impact businesses (defined as having high rates of growth in sales and employment) disproportionately contribute jobs in the economy (Haltiwanger, Jarmin and Miranda 2013; Kulick, Haltiwanger, Jarmin, Miranda 2016; Tracy 2011). A few recent studies also examine the relationship and growth patterns between non-employer to employer businesses. These studies find, for example, that non-employers have startup rates that are nearly three times the startup rates of employer firms, a significant number of new employer firms start as non-employer firms, and if non-employer startups hire, the bulk of hiring occurs in the first few years of existence

(Davis et al. 2007; Acs, Headd and Agwara 2009; Fairlie and Miranda 2016).⁸ Another strand of literature examines entrepreneurial survival rates (e.g. Phillips and Kirchoff 1989; Audretsch 1991; Audretsch Mahmood 1995; Robb and Farhat 2013; BLS 2017; SBA 2017). Recent estimates from the BLS (2017) indicate that 48 percent of new employer establishments survive after five years. None of these previous studies, however, use the full universe of startups and the entire history of non-employer and employer status to measure entrepreneurial job creation and survival. This may be an important omission in the literature because of the nearly 5 million non-employer business entities created each year in the United States.

Our paper also contributes more generally to the rapidly growing literature on entrepreneurship. This emerging field has struggled with finding adequate data and agreement on definitions of entrepreneurship. We create a new compilation of administrative data that captures the universe of business startups in the United States. These longitudinal administrative data allow for the exploration of many questions around entrepreneurial job creation, survival and growth, and allow for substantial flexibility in defining entrepreneurship. Additionally, the massive number of observations – an average of 5.4 million startups *each* year – allows for extremely detailed analyses of entrepreneurs. The administrative panel data also provides major advantages over cross-sectional data or panel survey data for measuring both job creation and exit rates per entrepreneur because it eliminates concerns over survivor, recall and attrition bias. A goal of this research project is to facilitate future research using the new compilation of administrative data on the universe of startups.

⁸ Using income tax return data, Carroll et al. (2000) find that among their sample of individuals who were sole proprietors in both 1985 and 1988 roughly one-third hired workers. They also found that 9 percent took on workers and 22 percent stopped hiring workers between the two years.

The rest of the paper proceeds as follows. In section II, we describe the data on startups. Section III presents the main empirical results on job creation, and Section IV presents the main empirical results on survival. Section V explores several potential explanations for underlying job creation and survival dynamics. Section VI explores questions related to heterogeneity in startup types and an alternative definition of entrepreneurship. Section VII concludes.

II. Data on Startups

To measure entrepreneurial job creation and survival rates, we create and use a new compilation of administrative panel data on the universe of business startups in the United States. We link the universe of non-employer firms to the universe of employer firms in the Longitudinal Business Database (LBD). To create the necessary links between non-employer and employer definitions, we update and expand the Integrated Longitudinal Business Database (iLBD). Beta versions of the iLBD have been used in previous work (e.g. Davis et al 2007; Fairlie and Miranda 2016) to study transitions between non-employer and employer business units, but these analyses were only for one or two years, a subset of industries, and/or not focused on startups.

For this paper, we combine the confidential and restricted access iLBD/LBD microdata that includes the universe of startups in the United States for several startup cohorts (i.e. 1995 to 2001 startup cohorts). The dataset that we use follows each startup cohort for several years after startup covering the years 1995 to 2010 (although we focus on seven follow-up years thus using data to 2008). The underlying iLBD is sourced from administrative income and payroll filings. The iLBD provides information on the universe of non-employer firms as well as a set of

identifiers that allow connecting them to the universe of employer firms in the LBD.⁹ The combination of the iLBD and the LBD then allows us to explore the connections between the two universes including transitions between the two. In combination with the LBD, the iLBD provides annual information that allows all businesses, employer and non-employer, to be followed over time. Because the iLBD contains links between the employer and non-employer universes, it is possible to accurately identify the point of startup for business units and each annual cohort of startups can be followed over time. A business entity can only be included in the startup cohort for that year if it is not found in previous years of the non-employer or employer universes.

When combined, the iLBD and the LBD provide a comprehensive view of patterns of non-employer and employer firms including the non-employers that hire employees in some future year. These data provide information at the point in time of hiring instead of less reliable retrospective information that might be collected through survey forms.¹⁰ Another advantage of the combined iLBD and LBD relative to many other datasets is that they contain administrative data on the universe of business units and thus suffer little from attrition problems. Examining job creation per startup over time using cross-sectional data is problematic because only surviving businesses are included. Attrition with longitudinal survey data is also a serious concern when exploring entrepreneurial dynamics. Even low annual rates of attrition lead to high rates of long-term attrition. It is thus difficult to estimate job creation over time by a cohort of startups using survey data.

⁹ For details about the LBD see Jarmin and Miranda (2002).

¹⁰ Employment in tax filings covers the payroll period of March 12th.

The transition between non-employer and employer status is especially important for examining job creation among all startups.¹¹ Identification of these transitions is challenging. The employer and non-employer administrative data are kept separate at the Census Bureau. Businesses in the United States are required to file separately income and payroll (employment) taxes. However, businesses may or may not use the same tax identifiers when filing their income and payroll reports.¹² Since the transition to employer status can only be identified by linking the income filing to the payroll filing, this can lead to broken linkages between the two. To resolve this problem the iLBD links the employer and non-employer businesses units by a variety of identifiers including the EIN, the Protected Identification Key (PIK), and the name and address of the owner or business.¹³ These enhanced linkages are tracked in the iLBD through longitudinal business identifiers, iLBDNUMs.

Every non-employer business that files taxes or a tax report is included in the iLBD. The iLBD contains information on the legal form; sole proprietor, partnership or corporation, the type of tax identifier; EIN or PIK, their revenue, and industry of activity. The file does not contain owner information although in the future this information could be linked from other sources.¹⁴ One concern is that the iLBD contains a large number of business activities that have no intention of hiring employees and represent consulting, contracting or hobby activities. But, these data provide a useful view of the universe of non-employer business units, and we are able

¹¹ The Kauffman Firm Survey (KFS) which provides data on a sample of roughly 4,000 non-employer and employer startups has also been used to study non-employer to employer transitions (Fairlie and Miranda 2016). Because of the underlying sampling frame of the KFS, however, the sample is skewed towards including employer firms.

¹² Non-employer businesses do not file payroll taxes.

¹³ The PIK is an individual identifier that replaces the Social Security Number (SSN) in all files at the U.S. Census Bureau. The PIK ensures no Census employee or researcher has access to SSNs. 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 PIK. If any of these change then it might not be possible to form a link. This is more likely when there is a change in legal form of organization at the time of the transition. For additional discussion of these issues see Davis et al. (2007).

¹⁴ The U.S. does not maintain a register of business owners. Administrative records allow identification of most but not all business owners. Owners of private corporations are particularly difficult to identify in administrative data.

to identify more growth-oriented businesses by conditioning on a few of the administrative variables in the iLBD. We explore this possibility below checking the findings with and without business entities registered as sole proprietors at startup.

All paid employees, including salaried officers and executives of corporations, who were on the payroll in the pay period including March 12 are measured (U.S. Census Bureau 2017). Employees on sick leave, holidays, and vacations are included. Proprietors and partners of unincorporated businesses are not included in employment counts. Businesses are included in the non-employer data only if they have zero payroll for the year.

The iLBD contains information on many business characteristics and outcomes of interest including revenue, location and industry of non-employers. When combined with the LBD it is possible to identify for the superset (including employers) the startup year, non-employer/employer status, number of employees, payroll, industry, exits, revenue, and additional information. See Fairlie, Miranda and Zolas (2016) for a listing of the variables contained in the iLBD and the LBD and whether the information is specific to non-employer or employer businesses.¹⁵

III. Job Creation by Startups

On average, 5.4 million businesses are started each year in the United States. This cohort of new businesses represents a large share of the total stock of business in the U.S. economy. During our sample period, the stock of businesses in the United States was 20-22 million indicating that startups comprise 25 percent of all business entities. The 5.4 million startups

¹⁵ The iLBD and LBD are confidential and restricted-access microdata files. They are accessible to researchers with an approval through Federal Statistical Research Data Centers (FSRDC). Information about the application process and more generally about FSRDCs is available at <http://www.census.gov/fsrdc>.

create an average of 3.0 million jobs in the initial startup year. Figure 1 displays total job creation for the entire startup cohort following job creation from the initial startup year to seven follow-up years after startup (see also Table 1). The total number of jobs created (net) declines slightly to 2.9 million by the fifth follow-up year and 2.7 million by the seventh follow-up year.

The 3.0 million jobs created by startups in the initial year represents roughly 3 percent of total employment by all businesses. Figure 2 displays the share of total U.S. employment created by startups in each year since startup. To calculate the startup employment share, total employment is averaged across all of the years following each cohort. Total U.S. employment ranged from 106 million to 116 million over the corresponding years.¹⁶ In the first follow-up year job creation among startups represents 2.8 percent of total employment by all firms. After five years the share of total U.S. employment by the average startup cohort is 2.5 percent, declining to 2.3 percent after seven years.

Although startups represent a small share of total employment they represent a large percentage of net job creation each year, especially in the first two years of existence. Figure 3 displays net job creation by startups and all other firms over time. Net job creation for all other firms is negative in every year, averaging 1.3 million job losses per year. Without the job creation contributions of startups through their first seven years of existence, net job creation would be negative in the United States.

These statistics indicate the importance of young firms to job creation in the United States. Using LBD microdata and focusing on the 2005 cohort, Haltiwanger, Jarmin and Miranda (2013) find that new (e.g. age 0) employer firms created 3.5 million net new jobs compared with a loss of 1 million net jobs for firms of all other ages (i.e. age 1 and over) combined. These

¹⁶ Total employment by all U.S. businesses is from U.S. Census Bureau (2017).

findings are similar to our estimates for the initial year contribution to job creation for the average startup cohort (which includes all startups).

Job Creation per Startup

We turn to examining the questions of i) How many jobs are created by each entrepreneur?, and ii) Do these jobs last over time? The answer to these questions are fundamental to how we think about entrepreneurship from policy, economic welfare, and theoretical perspectives. Figure 4 displays the number of jobs created by the average startup over seven follow-up years (see also Table 1). The average entrepreneur creates 0.56 jobs in the startup year. Average employment per entrepreneur does not disappear quickly: it is 0.53 five years after startup and 0.50 seven years after startup. All startups in a cohort are included in the denominator even if they exit. Administrative panel data on the universe of startups is essential for this calculation because we do not have slippage in job creation through survey response attrition or survival bias.

These patterns of job creation by the average entrepreneur reveal two important findings. First, job creation levels per entrepreneur are relatively low. Startups create an average of roughly $\frac{1}{2}$ job each. With these levels of jobs created per entrepreneur, it is difficult to design and run cost-effective programs to spur entrepreneurship for reasons of job creation. Second, although total levels of job creation might be viewed as relatively low, the jobs created by entrepreneurs do not disappear right away. The number of jobs created by the average startup only declines by 0.06 jobs, from 0.56 jobs to 0.50 jobs 7 years later. Net job creation by startups is relatively long lasting.

However, the reported estimates of job creation ignore the fact that entrepreneurs are effectively creating jobs for themselves. We focus on this question in the next section when we examine business survival rates. Even if entrepreneurs create jobs for themselves, if these jobs do not last long, they would not have a long-lasting effect on our measure of total job creation.

Payroll per Employee

From administrative payroll records, we can also examine how much employees are paid on average at each startup. Figure 4.2 displays average payroll per employee by years since startup. All payroll statistics are adjusted for inflation and reported in 2015 dollars. The average earnings per employee is \$31,600 in the startup year. Earnings per employee increase to \$33,100 in the first follow-up year and steadily increase in each follow-up year. By the fifth follow-up year, earnings per employee are \$37,400, rising to \$38,400 by year 7. Average salaries at startups are lower than more established businesses. Establishment level data from the U.S. Census Bureau indicate that over a similar time period, all business establishments in the United States paid an average of roughly \$45,000 per employee. The finding of lower wages paid at young firms relative to older firms is in line with previous work focusing on employer businesses (Brown and Medoff, 2003; Haltiwanger et al., 2012).

Regression Results

We now turn to an exploration of the factors associated with job creation among the universe of startups. To investigate this question we estimate the following equation:

$$(1) Y_{it} = \alpha + \sum_{s=1}^7 \delta_s D_{is} + \sum_{k=1}^{19} \beta_k D_{ik} + \gamma_t + \lambda_g + u_i + \epsilon_{it}$$

where Y_{it} is employment at firm i in year t , D_{is} is a set of dummy variables for years since startup for firm i , D_{ik} is a dummy variables for industry k , γ_t are fixed effects capturing each annual startup cohort, λ_g are zip code fixed effects, and $u_i + \epsilon_{it}$ is a composite error term. The main parameters of interest are δ_s which capture job creation in follow-up year s relative to the omitted startup year, and β_k , which captures job creation for industry k . Standard errors are clustered at the firm level to account for multiple observations per startup.

To estimate Equation (1), we include the full sample of firm/year observations even after exits. In the case of exits, we set employment to zero and include observations for all subsequent years for that firm. We thus treat a non-surviving startup as having no employment, which is similar to the idea of net job creation per startup over time. Because we have administrative data on all startups over time, we can rule out the concern that sample attrition is masking exits.

The regression includes fixed effects for every zip code in the United States. Thus, we are controlling for extremely detailed geographical areas. Time-invariant differences found across the United States in local business climates, entrepreneurial development policies, banking conditions, access to financial capital, income levels, consumer demand, housing markets, and many other factors are controlled for by the inclusion of these fixed effects. Although not reported in the table, we also control for the differences in job creation across startup cohorts. We do not find major differences across startup cohorts, and do not focus on that here.

Specification 1 of Table 2 reports estimates of Equation (1). After controlling for startup cohort years, industries and zip codes, we find that job creation increases slightly after startup and then declines slowly. The first follow-up year after startup job creation is slightly higher than at startup (+0.033 jobs). At startup, 0.56 jobs are created by the average entrepreneur. The fifth year after startup shows a slight decline of 0.06 jobs and the seventh year shows a decline of 0.09

jobs. These estimates are similar to those implied by the patterns displayed in Figure 4. The relatively constant or slight declining pattern across years since startup is not driven by differences in industries, startup cohorts or geographies.

Table 2 also reports coefficients by industry. Job creation levels differ substantially across industries (unadjusted job creation levels by industry are reported in Appendix Table 1). In all regressions reported here and below, “Other Services” is the left out category and has an average employment level of 0.25 jobs per startup. A few industries have employment levels that are 1-2 jobs higher: Management (+2.3), Manufacturing (+1.5), and Accommodation and Food Services (+2.9). Industries with the lowest job creation levels in addition to Other Services, which is the third lowest level, are Agriculture (-0.16), Real Estate (-0.04), Arts, Entertainment and Recreation (0.08), Transportation (0.14), and Professional (0.15).

IV. Survival Rates

Using the universe of startups, we explore the third question: How many entrepreneurs survive each year after inception? Figure 5 reports the number of startups surviving over the seven-year follow-up period from the representative startup cohort (see also Table 1). Of the 5.4 million startups, a large number disappear in each follow-up year. Nearly 40% of startups exit by year 1 (3.2 million startups survive) and nearly 60% exit by year 2 (2.3 million startups survive). After this initial shakeout, the exit rate starts to slow down. After five years, 1.1 million startups remain in operation and after seven years, 810,000 startups remain in operation. Figure 5.2 displays essentially the same information as Figure 5, but as survival rates for the average startup cohort. In all of our analyses of survival rates, we do not distinguish between business closures

and failures.¹⁷ Because of data limitations and to follow federal government convention, we focus on survival of the business entity.

Regressions for Survival Rates

We now turn to an exploration of the factors associated with survival among the universe of startups. To investigate this question we estimate the following equation:

$$(2) Y_{it} = \alpha + \sum_{s=1}^7 \delta_s D_{is} + \sum_{k=1}^{19} \beta_k D_{ik} + \gamma_t + \lambda_g + u_i + \epsilon_{it}$$

where Y_{it} is survival of firm i in year t (equal to 0 or 1), D_{is} is a set of dummy variables for years since startup for firm i , D_{ik} is a dummy variable for industry k , γ_t are fixed effects capturing each annual startup cohort, λ_g are zip code fixed effects, and $u_i + \epsilon_{it}$ is a composite error term. As before, the main parameters of interest are δ_s and β_k . Note that survival, $Y_{it} = 1$, in the startup year for all businesses, and thus the startup year is excluded from the regressions. Standard errors are clustered at the firm level to account for multiple observations per startup. Regressions are estimated with a linear probability model (marginal effects estimates for logit and probit models are similar and not reported).

To estimate Equation (2) we include the full sample of firm/year observations even after exits. In the case of exits, we set survival equal to zero and include observations for all subsequent years for that firm. Alternatively, we could estimate a hazard model for the length of the survival spell, but the typical advantages of hazard models such as addressing left and right censoring of spells and having multiple spells do not apply here. To simplify estimation with the restricted and confidential data with a large sample we estimate the regressions with a linear probability model (OLS) using all possible observations over the 8-year window for each startup.

¹⁷ See Headd (2003) and Parker (2009) for discussions on the limitations of focusing solely on business exits.

Similar to the employment regressions, the administrative data on startups rule out the concern that sample attrition is masking exits.

Specification 1 of Table 3 reports estimates of Equation (2). After controlling for startup years, industries and zip codes, we find that survival rates decrease sharply in the first couple of years and then taper off. Survival rates drop by 0.38 in the first follow-up year after startup. Two years after startup survival rates have dropped by 0.56. After five years post startup the survival rate drops 0.77. Controlling for geographic, startup year and industry differences does not change the finding of a strong downward trend in survival rates over years since startup.

In contrast to job creation rates by industry, survival rates do not differ substantially by industry (unadjusted job creation levels by industry are reported in Appendix Table 2). Other Services is the omitted category and has a survival rate of 42 percentage points over all years since startup combined. Most industries differ by 2 percentage points or less in either direction from this omitted category. Only a few industries differ notably from this level. The main exceptions are that the survival rate is 7.4 percentage points lower for Information, 6.6 percentage points lower for Administrative and Support, and 10.2 percentage points higher for Real Estate. But, overall, the differences are not large and survival probabilities are largely independent of industry.

V. Heterogeneity in the Underlying Dynamics of Job Creation by Startups

In this section, we explore several questions related to the underlying dynamics of job creation and survival among startups. First, we explore the question of why does the average number of jobs per entrepreneur remain relatively constant over years since startup. Patterns in the average number of jobs created per entrepreneur conceal a substantial amount of

heterogeneity in the underlying dynamics of job creation by startups, which might hold the answer. We explore four potential explanations for the relatively flat pattern: i) a large percentage of startups survive and these startups grow slowly, ii) a large percentage of startups survive and a small percentage of the survivors grow rapidly, iii) a small percentage of startups survive and a large percent of survivors grow steadily, and iv) a small percentage of startups survive and a small percentage of survivors grow very rapidly.

Because such a large percentage of startups exit in the first few years of operation, we can likely rule out the first two explanations due to the relatively flat level of job creation over time. To examine this directly, however, Figure 6 displays job creation per surviving startup and job creation per all startups over time. Job creation levels per *surviving* startup grow rapidly over time. At startup, the average startup employs 0.56 workers. Among surviving startups one year later, the average startup hires 1.1 employee. Seven years later, surviving startups hire an average of 3.3 employees each. These results are consistent with the strong “up or out” pattern of startup dynamics first noted among employer startups in Haltiwanger, Jarmin and Miranda (2013).

Overall, the strongly opposing patterns of increasing job creation among surviving startups and decreasing survival rates among startups mostly cancel each other out. This explains why total job creation from the startup year to five years later only changes by 0.03 employees (5 percent). Even seven years later, it only changes by 0.06 employees (11 percent).

Regressions Conditioning on Survival

Given the strong pattern of employment growth among surviving startups, we examine the determinants of job creation conditional on survival. Are the characteristics associated with job creation per startup different when focusing on only *surviving* startups? To investigate this

question we estimate Equation (1) including only surviving startups. We condition on survival in that year. In this case, we exclude all annual observations after firm exit. We are thus estimating a model that measures net job creation per *surviving* startup.¹⁸

Specification 2 of Table 2 reports estimates for the conditional model. The same sets of variables and controls are included in the regression. The sample size is now smaller and the sample mean of the dependent variable is larger. Similar to the unconditional sample estimates we do not find a strong pattern across startup cohorts. Estimates from the conditional model indicate a different time series pattern for job creation. Conditioning on survival the number of jobs per startup increases steadily since inception of the business. One year after startup, average employment increases by 0.46. Five years after startup, average employment increases by 1.81 and seven years after startup employment increases by 2.5.

The industry patterns generally follow the same patterns as the unconditional sample estimates. We continue to find that the industries with the highest levels of conditional job creation are Manufacturing (+3.6), Management (+5.1), and Accommodation and Food Services (+6.9). Industries with the lowest levels of job creation conditional on survival in addition to Other Services, which is the third lowest level, are Agriculture (-0.23) and Real Estate (-0.31).

Most of the coefficients are 2 to 3 times the absolute magnitude of the unconditional coefficients. The finding that the industry coefficients from the conditional and unconditional samples line up reasonably well suggests that differences in survivor rates are not driving the overall differences. This finding is consistent with the finding from Table 3 that survival rates do not differ substantially across industries. The unconditional model includes extra zeros for

¹⁸ We considered estimating a selection model that simultaneously estimates the exit probability and employment level, but could not identify a credible instrument that affects exits, but is uncorrelated with unobservables in the employment equation. Thus, we estimate a conditional model that focuses on the employment decision for only surviving startups to complement the unconditional model that captures both exit and employment.

employment when a startup exits. If exit rates over time are reasonably similar, then industries will have a similar number of zeros included in the unconditional model thus resulting in a uniform shift upward in absolute magnitude in coefficients.

Movement between No Employment, Employment and Exit

Another important type of underlying heterogeneity in the dynamics of startups is the movement between not having employees, having employees and exits. Only a small share of all startups hire employees in the initial year, but many non-employer startups transition to hiring employees over time. Because of data limitations these movements have not been previously examined in detail.

Figure 7 displays the evolution of startups over time across the trichotomy of not hiring employees, hiring employees, and exits. The percentages of the startup cohort that hire employees, do not hire any employees and have exited in the startup year and over the seven follow-up years are reported. Eight percent of the startup cohort hire employees in the initial year with the rate declining steadily over time. By the seventh follow-up year, 4 percent of the startup cohort hires employees. In contrast, 91 percent of the startup cohort have no employees in the initial year and by the seventh follow-up year 11 percent have no employees. The decline in the percentage of startups hiring employees or not hiring employees is primarily driven by the rapidly increasing percentage of startups that exit. By the seventh follow-up year, 85 percent of the startup cohort has exited.

Focusing on only surviving startups, there is a constant shift from having no employees to having employees over time. At startup, 9 percent of the cohort has employees. In the first follow-up year, this jumps to 14 percent and then steadily increases each year since startup. After

seven follow-up years, 28 percent of the surviving startups hire employees. Interestingly, these startups with employees did not all start with employees. In fact, 19 percent of startups with employees at year 7 started with no employees.

Distribution of Employment among Startups

The results displayed in Figure 6 indicate that there is rapid growth in average employment levels among surviving startups. An important question is whether the strong upward trend in average employees per surviving startup is due to a few very fast growing survivors (“gazelles”) or a larger number of steadily growing survivors? To investigate this question, we examine the distribution of employment size for all startups with employees. Table 4 reports the percentage of startups by employment size by follow-up years. Startups generally start out small with 86 percent having 1-4 employees at startup out of the 9 percent having any employees at startup. At startup, 9 percent of new businesses with employees hire 5-9 employees, and 3 percent hire 10-19 employees. Very few startups hire 20 or more employees at startup. Over time, however, employment size increases. After seven follow-up years, among surviving startups with employees, 20 percent hire 5-9 employees and 12 percent hire 10-19 employees. Another 11 percent hire 20 or more employees. Overall, these results point to a steady shift to larger employment sizes among startups. The upward shift in the size distribution of startups is very smooth as seen more easily in Appendix Figure 1. The increase in average net jobs per surviving startup is not driven by a few startups becoming wildly successful, but instead by steady employment growth among many startups. This runs counter to the argument that one or two large retailers drive everything.

Together these findings tell a story of low survival rates among entrepreneurs and low rates of hiring any employees, but those that do survive and hire employees show steady growth in employment levels. In other words, the strong growth in average employment per surviving startup is not driven by a few outliers with extremely rapid growth rates and massive employment levels over the first several years since startup.

VI. Heterogeneity in the Definition of an Entrepreneur

In this section, we explore two broad questions about the definition of an entrepreneur. First, do non-employer startups create jobs one, two or more years later, and if so, do they make a sizeable contribution to job creation in the United States? The previous literature has not been able to answer this question because of data limitations. Second, we explore the related question of whether the low levels of job creation per entrepreneur and survival rates found above are simply due to an overly inclusive definition of entrepreneur (i.e. using the entire startup universe). If we restrict the population of startups to be less inclusive and require a stronger signal of commitment by entrepreneurs at startup, do we continue to find low levels of job creation and survival?

All of the analyses of job creation and survival dynamics thus far use the most inclusive definition of entrepreneurship possible – the universe of business startups in the U.S. economy. But there is substantial heterogeneity that exists across business types at startup. To investigate this heterogeneity, we start by focusing on the main distinction between startup types, which is whether they are non-employers or employers at the time of startup. The distinction arises primarily because of how the two types of businesses are treated in Census data. As noted above, non-employer businesses are tracked by PIKs and employer businesses are tracked by EINs.

Using the iLBD we can identify whether the first observation in the administrative panel data is non-employer or employer. This is not possible by only using the administrative LBD panel data, which has been used in many previous studies, because it does not include the pre-employment histories of each employer firm.

Government Focus on Employer Startups

Previous research and statistics on entrepreneurs, startups or small businesses published by the U.S. Census Bureau, U.S. Bureau of Labor Statistics and U.S. Small Business Administration focus almost exclusively on new *employer* businesses or new *employer* establishments. Published numbers from these sources or numbers that can be calculated from published sources, as expected, indicate higher levels of job creation and survival than presented above. In the well-publicized “Frequently Asked Questions about Small Business” report, the SBA reports job creation and survival rates.¹⁹ The SBA reports that the average number of employees per new employer firm is roughly 6 percent. The SBA also reports that an average of 79 percent of new employer establishments survive one year later and roughly half of all new employer establishments survive five years or longer. These statistics are derived from underlying Census or BLS data.

Recently, the BLS started publishing aggregate data under their “Entrepreneurship in the U.S. Economy” series based on the Business Employment Dynamics (BED) series.²⁰ Statistics on the number of establishments that are less than 1-year old are used to measure Entrepreneurs. Averaging over many cohort years, these data indicate that 48 percent of new employer

¹⁹ See <https://www.sba.gov/sites/default/files/advocacy/SB-FAQ-2017-WEB.pdf>.

²⁰ See <https://www.bls.gov/bdm/entrepreneurship/entrepreneurship.htm>. The BED is generated from the Quarterly Census of Employment and Wages (QCEW) database. The underlying QCEW data come from employment and total wage information covered by state and federal unemployment insurance programs.

establishments survive at least five years. Job creation can also be calculated from reported BED data and indicate that new employer establishments hire an average of 5.7 employees in the first year. Unfortunately, only the first year is available from published sources by the BLS.

The U.S. Census Bureau publishes statistics on the “Number of firm startups” based on the Business Dynamics Statistics (BDS) series. Job creation and survival rate numbers are not reported, but can be calculated for new employer businesses.²¹ The BDS is created from the underlying Longitudinal Business Database (LBD), which includes only employer businesses. Firm startups are defined as those employer businesses with age equal to 0. Thus, in this case and with recent research analyzing the underlying data entrepreneurial activity is represented as new *employer* businesses (e.g., Decker et al. 2014). But, the focus is on new businesses and not new establishments, which is an advantage of the BDS over the BED data for examining startups. Using information from multiple years and age of businesses, startup cohorts can be tracked over time. Using this information, we calculate that employer business startups create an average of 6.1 jobs in the first year and 4.7 jobs in the fifth year after startup.²² Survival rates are 76 percent survive after one year, 65 percent survive after 2 years, and 46 percent survive after 5 years.

A non-government source of data on startup survival rates is the Kauffman Firm Survey (KFS). The KFS follows a sample of roughly 5,000 non-employer and employer startups from the 2004 cohort. For this sample of startups, roughly 90 percent survive one year and 55 percent survive 5 years after startup (Robb and Farhat 2013). The underlying sampling frame of the KFS, however, is skewed towards including employer firms, which may also explain why these estimates of survival rates are much higher than for the universe of startups.

²¹ As noted in Haltiwanger, Jarmin and Miranda (2013) prior to the release of the published BDS there was no age information in publically available data leading to the perceived finding of an inverse relationship between firm size and growth in the data.

²² For employer business data by firm age see https://www.census.gov/ces/dataproducts/bds/data_firm.html.

Contributions of Non-Employer Startups

Given the previous focus on employer startups, it is important to understand what we lose by not including non-employer startups. In particular, do non-employer startups create jobs in the years following startup, and how many jobs do they create? Figure 8 displays the number of jobs created by the average employer startup and the average non-employer startup over time. Note that non-employer startups that do eventually hire an employee are classified as employer firms in those years but they are not classified here as employer startups. Job creation per non-employer startup is substantially lower than job creation per employer startup in the follow-up years, as expected. The average employer startup creates 6.2 jobs at startup falling to 4.2 jobs seven years later. Seven years later, the average business that started without employees has 0.2 employees.

Although these statistics appear to indicate that employer startups generate essentially all jobs among startups, this is not the case. There are many more non-employer startups than employer startups. Non-employer startups represent roughly 90 percent of all startups. The total number of existing non-employer businesses also dwarfs the total number of existing employer businesses. Appendix Table 1 reports the number of existing non-employer and employer firms. On average there are four times as many non-employers as there are employer firms in the United States.

Examining total jobs created by all employer startups vs. all non-employer startups reveals a somewhat different pattern than jobs created per entrepreneur. Figure 9 displays the total number of jobs created by employer and non-employer startups over time. The total number of jobs created by non-employer startups steadily increases relative to the total number of jobs

created by employer startups over time. Even only one year following startup, non-employer startups hire nearly 500,000 employees. Employer startups hire 3.1 million, which is considerably higher. But, seven years after startup, we find that non-employer startups hire 600,000 employees and employer startups hire 2.1 million employees.²³ Non-employer startup total job creation increases from 14 percent of the total one year after startup to 22 percent of the total seven years after startup.

Additional Arguments for the Inclusion of Non-Employer Startups

The inclusion of non-employer startups is also important for conceptual reasons. A large part of the entrepreneurship literature takes an individual approach to analyzing entrepreneurship. For example, classic studies of the entrepreneur such as Knight (1921), Schumpeter (1934) and more recently Evans and Jovanovic (1989) do not limit the definition of entrepreneurs to include only business ventures with employees. Additionally, most previous empirical studies of entrepreneurship using a vast range of different datasets do not distinguish between entrepreneurs with or without employees (for a few examples see Evans and Leighton 1989; Holtz-Eakin, Joulfaian and Rosen 1994; Blanchflower and Oswald 1998; Fairlie 1999; Hamilton 2000; Fairlie and Robb 2008; Lafontaine and Shaw 2016; Levine and Rubinstein 2016, and review in Parker 2009).

Many non-employer businesses are also extremely successful. The latest non-employer data reported by U.S. Census Bureau indicates that there are nearly 300,000 non-employer businesses with ½ million or more in annual revenues in 2014. The latest U.S. Census Bureau

²³ Comparing the jobs created by surviving non-employer and surviving employer startups over time we find that the jobs created by the two types of startups in terms of payroll per employee do not differ. Average pay per employee is very similar between non-employer and employer startups.

Survey of Business Owners (SBO) data indicate that there are nearly 250,000 non-employer businesses with ½ million or more in annual revenues in 2012. Part of the entrepreneurial folklore especially in high-tech is how many very successful entrepreneurs started in garages without employees.

Thus, leaving out non-employer startups may obscure a relevant dimension of early-stage entrepreneurial dynamics in the United States. In particular, it would be misleading to exclude all non-employer businesses to answer the question of how many jobs are created by the average entrepreneur. Not only does it affect the denominator in this calculation, but many non-employer startups become employer firms and make substantial contributions to job creation, sometimes several years after startup. Additionally, inclusion of non-employer startup data is important for accurately measuring survival rates and identifying the cohort year and years since startup as many young employer firms begin as non-employer startups.

Restricting the Non-Employer Startup Population

We next examine whether the low levels of job creation per entrepreneur and survival rates found above are simply due to an overly inclusive definition of entrepreneur (i.e. using the entire startup universe). If we restrict the population of startups to be less inclusive and require a stronger signal of commitment by entrepreneurs at startup, do we continue to find low levels of job creation and survival?

There are essentially two data-driven primary classifications of business entities by the U.S. Census Bureau and four legal form subclassifications within the non-employer universe:

- 1) Employer startups
- 2) Non-employer startups

2.1) Incorporated: business granted a charter recognizing it as a separate legal entity having its own privileges and liabilities distinct from those of its members.

2.2) S-Corporation: A form of corporation where the entity does not pay any federal income taxes, and its income or losses are divided among and passed to its shareholders (which are reported on their own individual income tax returns).

2.3) Partnership: unincorporated business where two or more persons join to carry on a trade or business with each having a shared financial interest in the business.

2.4) Sole proprietorship: unincorporated business with a sole owner.

Instead of excluding all non-employer startups, we want to use this information to narrow down the definition of an entrepreneur. The goal is to propose an alternative definition of entrepreneurship that might serve as a reasonable upper bound on job creation per entrepreneur and survival rates. We include all non-employer startups that are incorporated, S-corporations or partnerships, but exclude sole proprietorships. In each of these cases there is a much stronger business registration requirement than for sole proprietorships. Also, consultants and contract workers will most likely show up as sole proprietorships. These work arrangements are technically classified as business entities in the data because of treatment in the tax code, but they do not fit the theoretical concept of an entrepreneur. They receive a 1099 form from a business and do not have to do anything else. Unfortunately, however, using this approach will result in the loss of some growth-oriented sole proprietorships that eventually hire employees.

This approach is in line with recent work that refines the definition of the entrepreneur. For example, Guzman and Stern (2016) use characteristics at founding such as how the firm is organized (e.g., as a corporation, partnership, or LLC, and whether the company is registered in Delaware), how it is named (e.g., whether the owners name the firm eponymously after themselves), and how the idea behind the business is protected (e.g., through an early patent or

trademark application) to identify high potential startups.²⁴ They note that although new businesses can be organized as sole proprietorships, more formal registration is a useful prerequisite for growth and includes benefits such as limited liability, tax benefits, the ability to issue and trade ownership shares, and credibility with potential customers. Levine and Rubinstein (2016) separate the incorporated and unincorporated self-employed in the CPS and NLSY to identify “entrepreneurs” and “other business owners.” They demonstrate that the incorporated self-employed engage in activities requiring strong non-routine cognitive abilities, tend to be more educated, score higher on learning aptitude tests, exhibit greater self-esteem, engage in more illicit activities when young, and experience a large increase in earnings relative to wage/salary work.

Figure 10 displays the total number of jobs created by startups and sole proprietorship startups over time. The total number of jobs created by this more restrictive population of startups rises from 3.1 million in the startup year to 3.4 million in the first follow up year. Total net job creation then declines steadily, reaching 2.4 million in the seventh follow-up year. Excluding sole proprietors results in the loss of 229,000 jobs in the first follow-up year to 296,000 jobs in the seventh follow-up year (which is roughly half of the jobs created by all non-employer startups).

As expected, the bigger effect from excluding sole proprietor startups is on the measure of job creation per entrepreneur. The numerator (total number of jobs) is smaller, but the real change is a much smaller denominator (total number of entrepreneurs). Figure 11 displays the number of jobs created by the average “hybrid” startup (non-employer and employer startups excluding sole proprietors) and the average sole proprietor startup over time. Job creation per

²⁴ Their sample covers 15 states capturing roughly 50 percent of the economy.

hybrid startup is higher than job creation per all startups in the follow-up years. The average hybrid startup creates 2.3 jobs at startup, rising to 2.5 jobs one year later, and then steadily declining to 1.8 jobs seven years later. Seven years later the average sole proprietor startup hires less than 0.1 employees.

We also estimate regressions for unconditional and conditional job creation that exclude sole proprietor startups. Specification 1 of Table 5 reports estimates from the unconditional model, and Specification 2 reports estimates from the model in which we condition on survival in that year. The same sets of variables and controls are included in the regressions. The sample size is now smaller and the means of the dependent variables are larger. We find many similarities between the results. The years since startup and industry coefficients generally follow the same patterns. One difference, however, is that in the unconditional model we do not see the slight drop off in employment levels over years since startup as we did for the full universe of startups. Employment levels increase slightly immediately after startup and then plateau in subsequent follow-up years. Conditioning on survival, the coefficients are similar. Among industries, one major change is that Management went from a relatively low job creator with the universe of startups to one of the highest job creators after removing sole proprietor startups. This might be due to Management having a relatively large percentage of contract work. See Appendix Table 4 for the full industry breakdown.

We can certainly expect estimates of job creation per startup to be higher if all non-employer startups are excluded. On the other hand, many non-employer startups grow and ultimately hire employees many years later underestimating counts of total jobs created per startup cohort. Conditioning on a subset of non-employer startups seeks to remedy these potential biases.

Survival Rates

As expected, we find that survival rates are higher among the more restrictive group of startups, but only slightly. Figure 12 displays survival rates for all startups, hybrid startups, and sole proprietor startups. Although sole proprietor startups have lower survival rates, their inclusion is not the primary reason that survival rates are low among the universe of startups. One year after startup, 68 percent of hybrid startups survive. This is higher than for the universe of startups (59 percent) and sole proprietor startups (57 percent), but the difference of roughly 10 percentage points is not extremely large. The 10 percentage point difference in survival rates is also fairly consistent across years since startup. Five years after startup, the survival rate for hybrid startups is 29 percent, compared with a survival rate of 21 percent for the universe of startups and 19 percent for sole proprietor startups.

Specification 2 of Table 3 reports regression results excluding sole proprietor startups. The same sets of variables and controls are included in the regression. The coefficient estimates do not change substantially. For the years since startup, the coefficients in fact are very similar. We find the same pattern of a rapid decline in survival rates and tapering off after that. For industries, we continue to find only small differences in survival rates across industries. Excluding sole proprietor startups from the “entrepreneur” sample does not change the findings regarding industry differences except for a couple of exceptions. Agriculture shifts from being negative 4.5 percentage point to zero, and Real Estate becomes larger from 10.2 percentage points to 16.5 percentage points. See Appendix Table 5 for the industry breakdown.

Lower and Upper Bounds on Job Creation and Survival

The inclusion or exclusion of sole proprietor, non-employer startups is an important decision in measuring entrepreneurial job creation and survival. Instead of taking a stand on whether entrepreneurship is best measured by the universe of startups or our new hybrid definition of startups we consider the two measures as lower and upper bounds, respectively.

Table 6 presents average jobs per entrepreneur using the full universe of startups as a lower bound and the hybrid subpopulation of startups as an upper bound. At startup, the lower and upper bounds for job creation per entrepreneur are 0.56 and 2.25, respectively. Five years after startup the lower to upper bound range for jobs per entrepreneur is 0.53 to 2.02.

Table 6 also presents upper and lower bounds for entrepreneurial survival rates using the full universe of startups and subpopulation of hybrids. One year after startup, 59 to 68 percent of entrepreneurs survive. This drops rapidly to 41 to 52 percent in the second year after startup and to 21 to 29 percent five years after startup.

Following a few recent studies, we restrict the definition of entrepreneur. On one hand, we lose some total jobs created, but job creation per entrepreneur is now higher. Also, survival rates are not that different, and the trend in job creation over years since startup is roughly similar.

VII. Conclusions

We create a panel dataset of startups that represents a new compilation of existing administrative data covering the universe of startups in the United States. Our analysis of these data produces several novel findings on entrepreneurship and job creation that have important implications for policy and our understanding of entrepreneurship. We summarize five key broad implications from the results.

First, entrepreneurs make major contributions to total job creation in the United States. We find that each annual cohort of startups creates a total average of 3.0 million jobs in the startup year, and employs a total of 2.9 million workers five years later. Without the job creation contributions of startups through their first several years of existence, job creation by all businesses would be negative in most years in the United States. We also find that non-employer startups (almost entirely excluded in previous work) make substantial contributions to job creation. Non-employer startups create an average of 600,000 jobs seven years after startup representing one-fifth of total employment by all startups. Identifying the non-employer histories of startups captures an important dimension to early job creation dynamics among entrepreneurs in the United States.

Second, policymakers and governments need to be careful about promoting entrepreneurship. Although startups make enormous contributions to total job creation in the U.S. economy, the contributions are mostly driven by the sheer number of new businesses created each year (approximately 5.4 million). Job creation is not high per entrepreneur – we find that using our most inclusive definition of entrepreneurship the average startup employs roughly 0.5 workers. This suggests that we should revise the fundamental question about job creation to “How many entrepreneurs does it take to create a job?” To be sure, when we exclude sole proprietor startups to create a more restrictive definition of entrepreneurship, job creation rates per startup are higher. We find that the average startup creates from 2.3 jobs at startup and 2.0 jobs five years later. Although the most reasonable definition of entrepreneurship is likely to lie somewhere between the two and closer to the lower bound estimate, these estimates do not imply high levels of job creation per entrepreneur. Therefore, public policies attempting to spur business creation need to be realistic about how many jobs can be created by new entrepreneurs.

Furthermore, with these levels of job creation per entrepreneur, programs to spur entrepreneurship will most likely have to be low cost or primarily target high-growth entrepreneurs to end up with a positive benefit/cost ratio (at least in terms of generating jobs). On a more positive note, however, net job creation by entrepreneurs is persistent – jobs are only 10-11 percent lower five to seven years after startup.

Third, in a broader sense job creation by entrepreneurs is higher because entrepreneurs create jobs for themselves and those jobs are not counted as employees in the data. Although the “entrepreneurs create jobs for themselves” argument is often made in the policy arena, the results presented here indicate that business ownership jobs do not last very long. We find extremely high exit rates among the universe of startups and even among our more restrictive population of startups. We find that only 41-52 percent of startups survive two years after startup, and 20-30 percent survive five years after startup. Furthermore, we find somewhat surprisingly that all major industries have high exit rates, and popular businesses such as restaurants have survival rates of only 21-29 percent five years after startup. The potential loss of business owner jobs should also be included in the economic welfare calculus for entrepreneurship policies.

Fourth, average patterns conceal a substantial amount of heterogeneity in the underlying dynamics of job creation and survival by startups along several dimensions explored here. We test several hypotheses for why the average number of jobs per entrepreneur remains relatively constant over years since startup and find that although startups have extremely high exit rates, the resulting job losses are nearly offset by the opposing patterns of strong employment growth among surviving startups and the large number of non-employer startups eventually hiring employees. This rapid growth in job creation among survivors is also not driven by a few extremely successful startups, but instead by a continual upward shift in the employment size

distribution. Turning to heterogeneity across startup types, we find that non-employer startups make sizeable contributions to employment several years after startup (22 percent of jobs seven years later). Instead of excluding all non-employer startups, we propose an alternative “upper bound” measure of job creation and survival among entrepreneurs that excludes sole proprietor non-employer startups. Job creation rates per entrepreneur are higher, but survival rates are only slightly higher. Examining heterogeneity across industries, we find that there are industries that are job creators – Management, Manufacturing, and Accommodation and Food Services have average employment levels that are 1-2 jobs higher. Further research should focus on why some startups grow rapidly and others do not, and whether government policies should target specific industries.

Finally, the analysis of startup data sheds new light on the fundamental nature of entrepreneurship. Given the low levels of job creation per startup and high exit rates, much of entrepreneurship as measured as the universe of startups is likely to be motivated by job independence, contract/consulting work, schedule flexibility, or being part of the gig economy instead of creating innovative products, services and jobs (i.e. Schumpeterian entrepreneurship). The administrative data do not include information on individual motives for creating a business, but it does appear that entrepreneurship is more about creating *a job* than creating *jobs*, and many of the business ownership jobs created are short-term, perhaps to help smooth out underemployment or unemployment spells. The newly compiled data on the universe of U.S. startups alone, or linked with other government data sources, has much potential for future research on these questions and additional ones. Further research using these data to evaluate the cost effectiveness of the multitude of proposed and existing policies to encourage entrepreneurship is especially needed.

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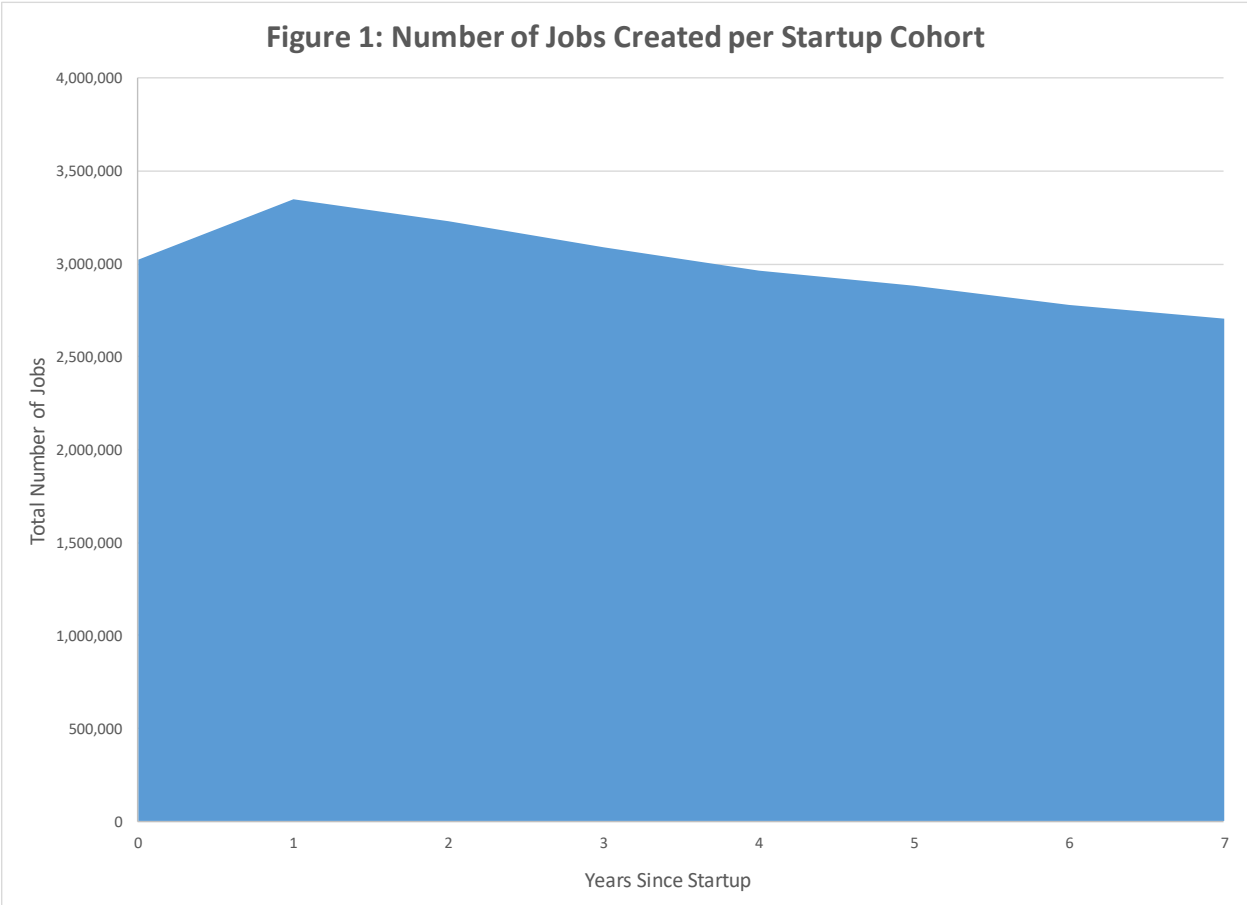
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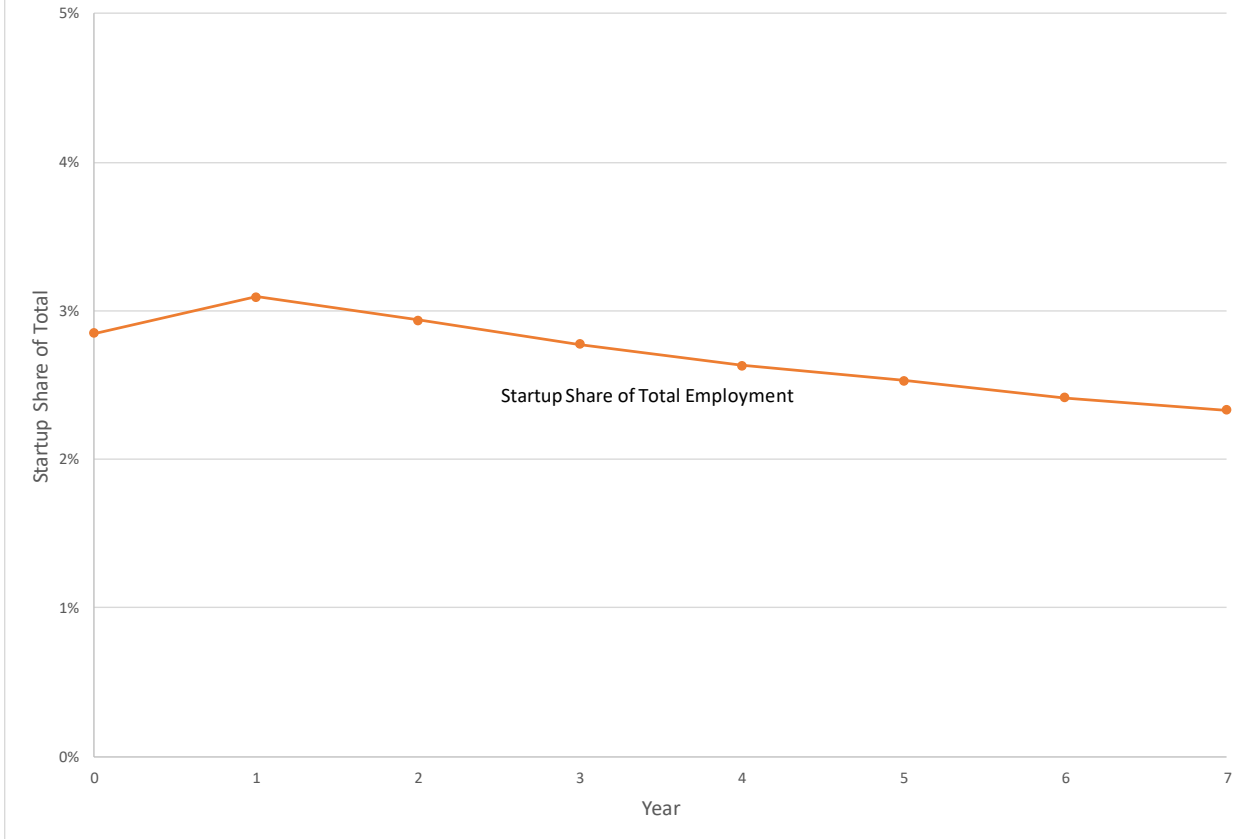
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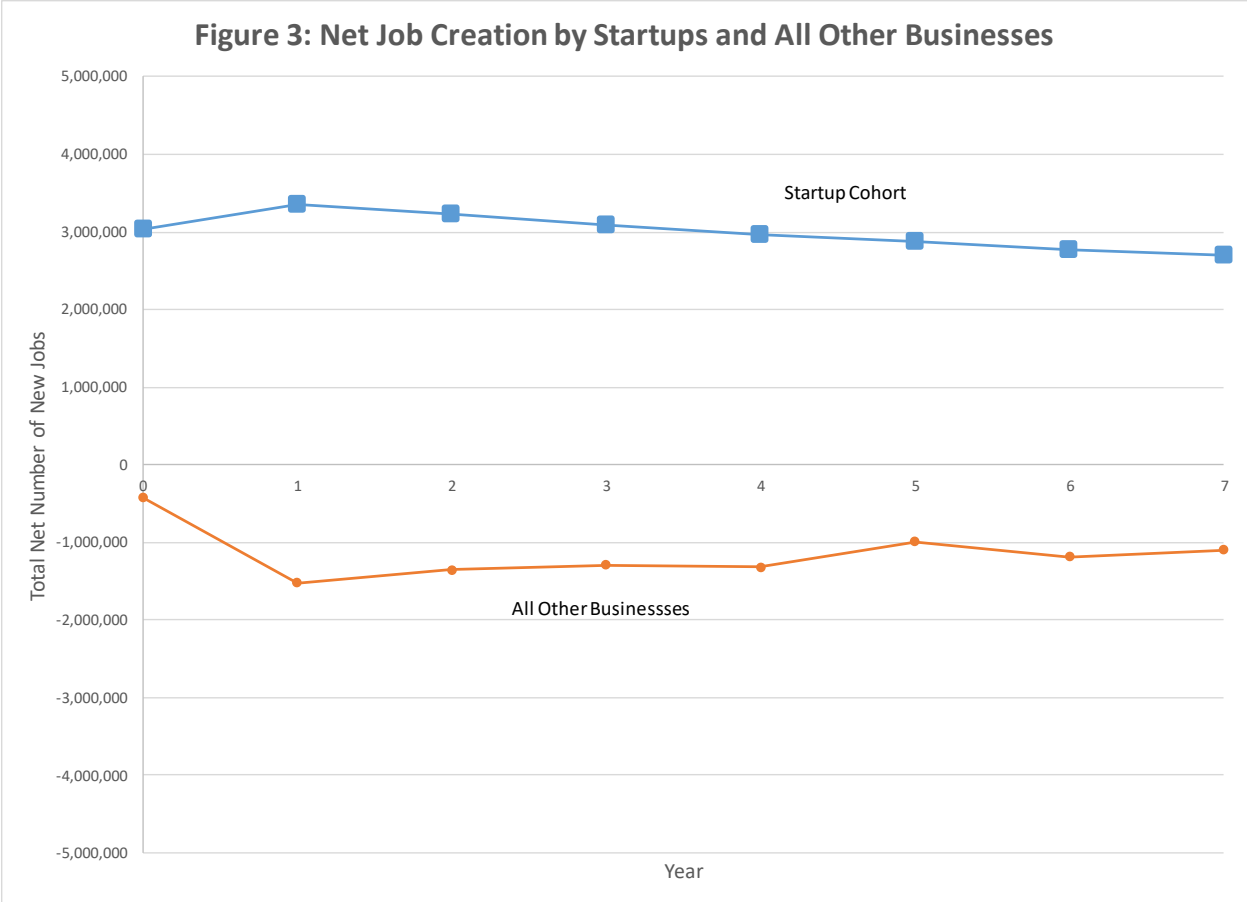


Source: Authors calculations of combined iLBD and LBD files.

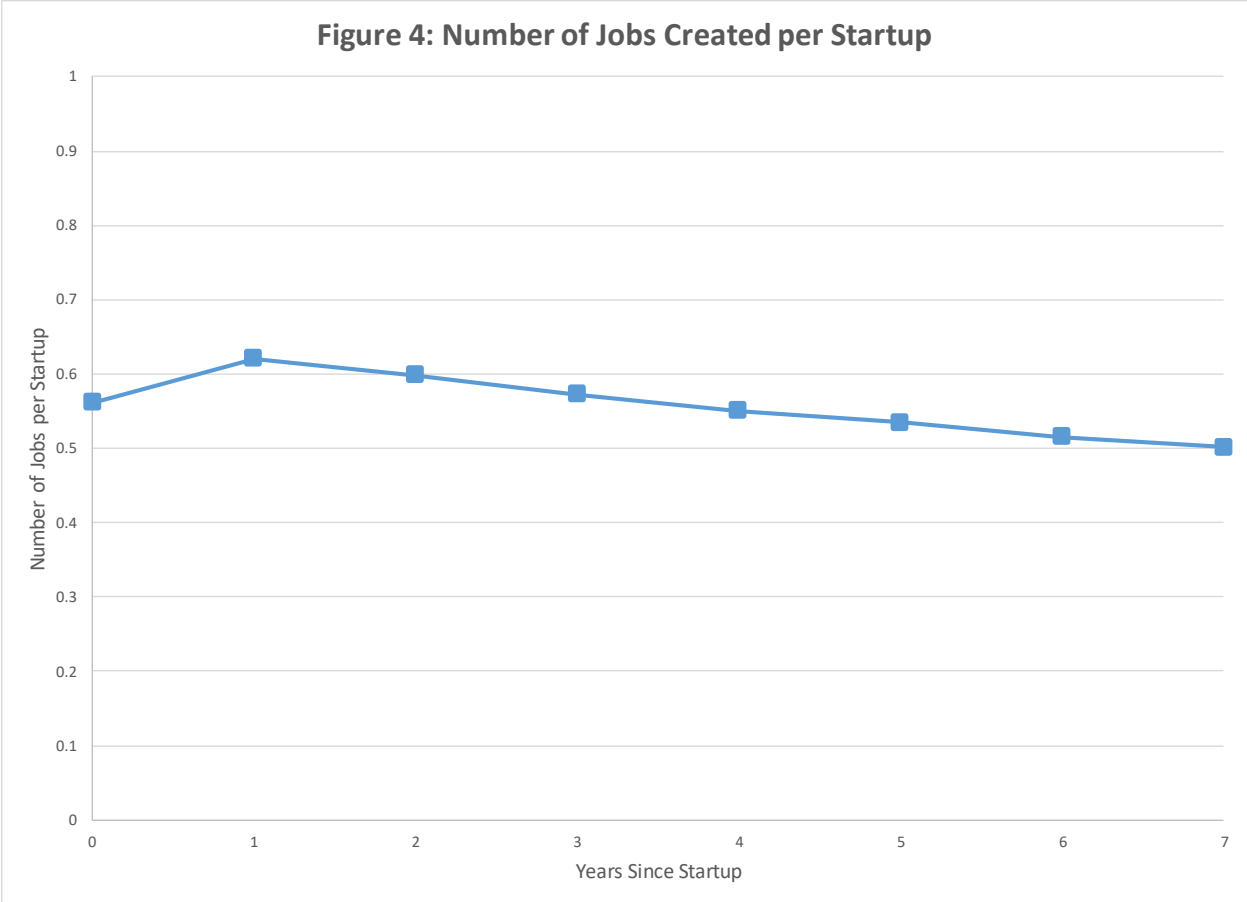
Figure 2: Share of Total U.S. Employment by Startups



Source: Authors calculations of combined iLBD and LBD files.

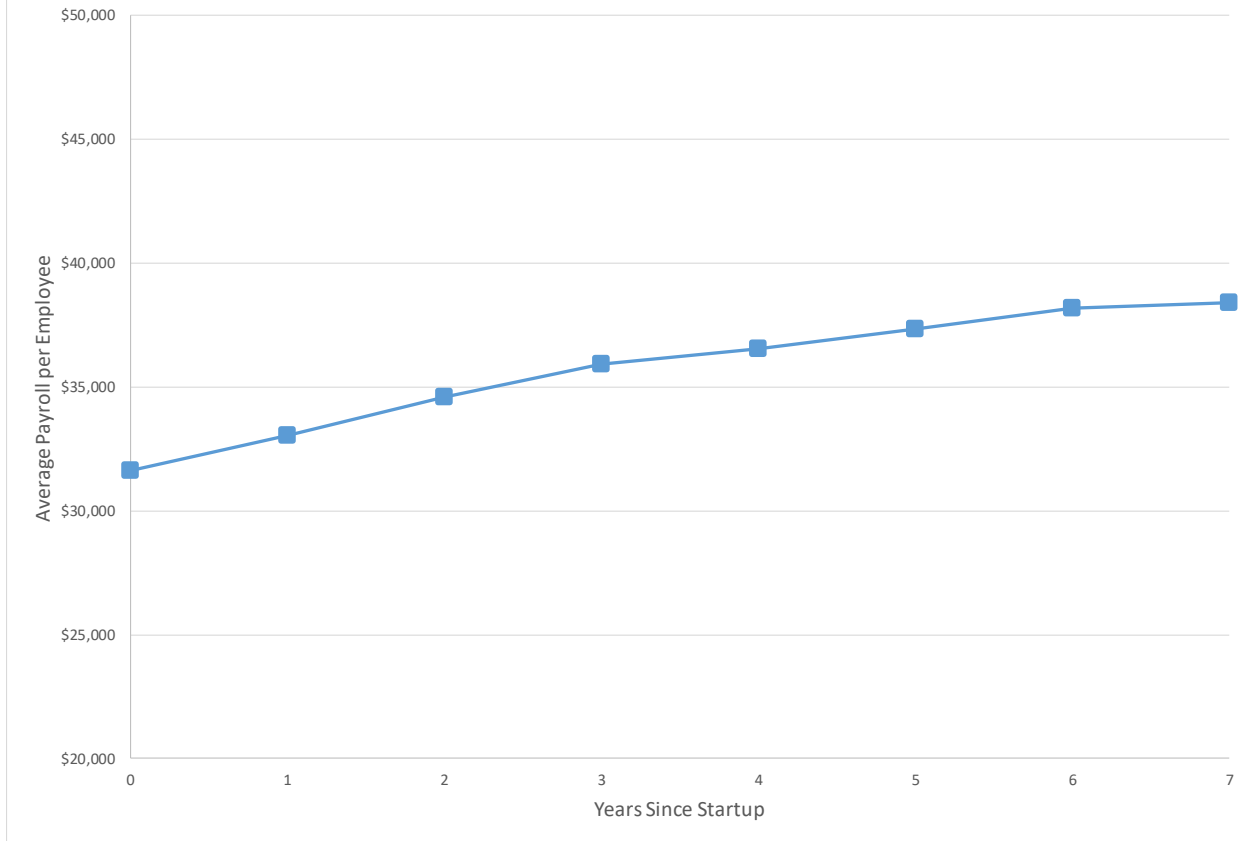


Source: Authors calculations of combined iLBD and LBD files.



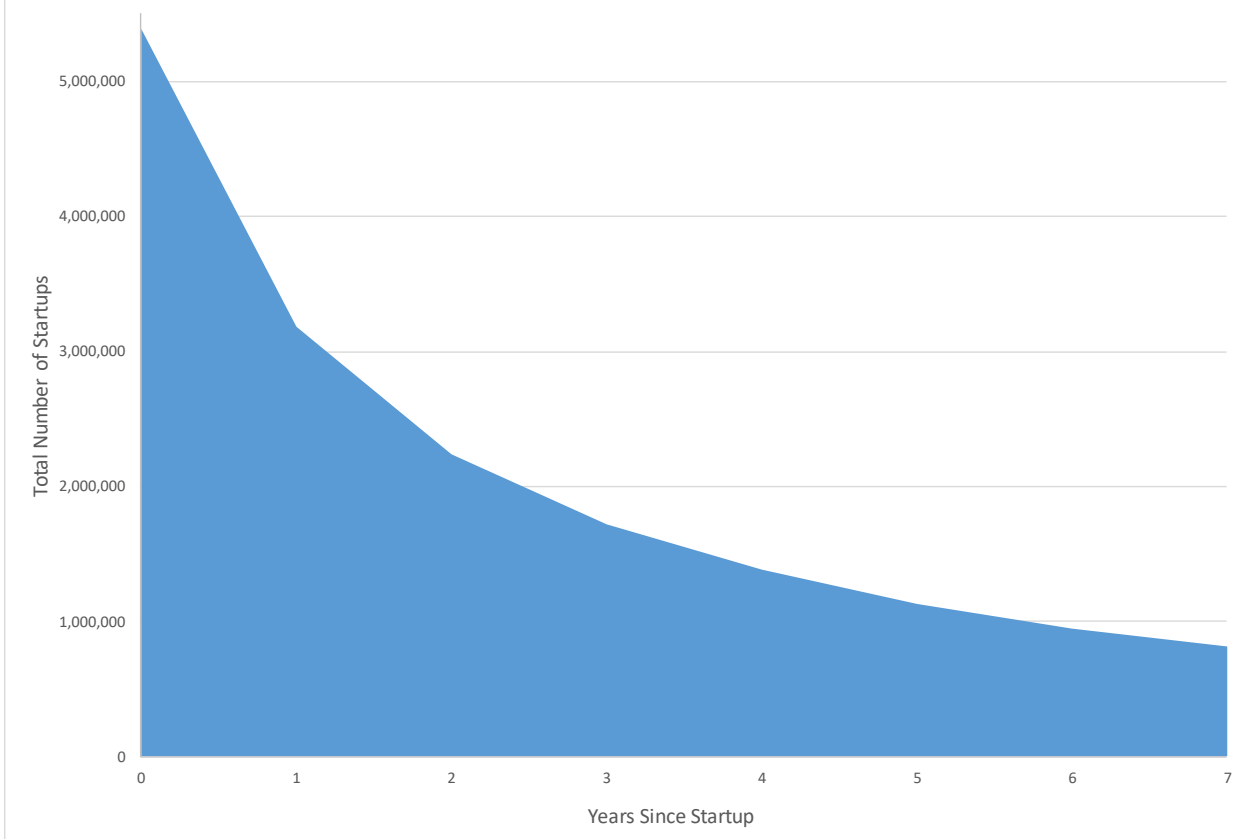
Source: Authors calculations of combined iLBD and LBD files.

Figure 4.2: Average Payroll per Employee by Startups

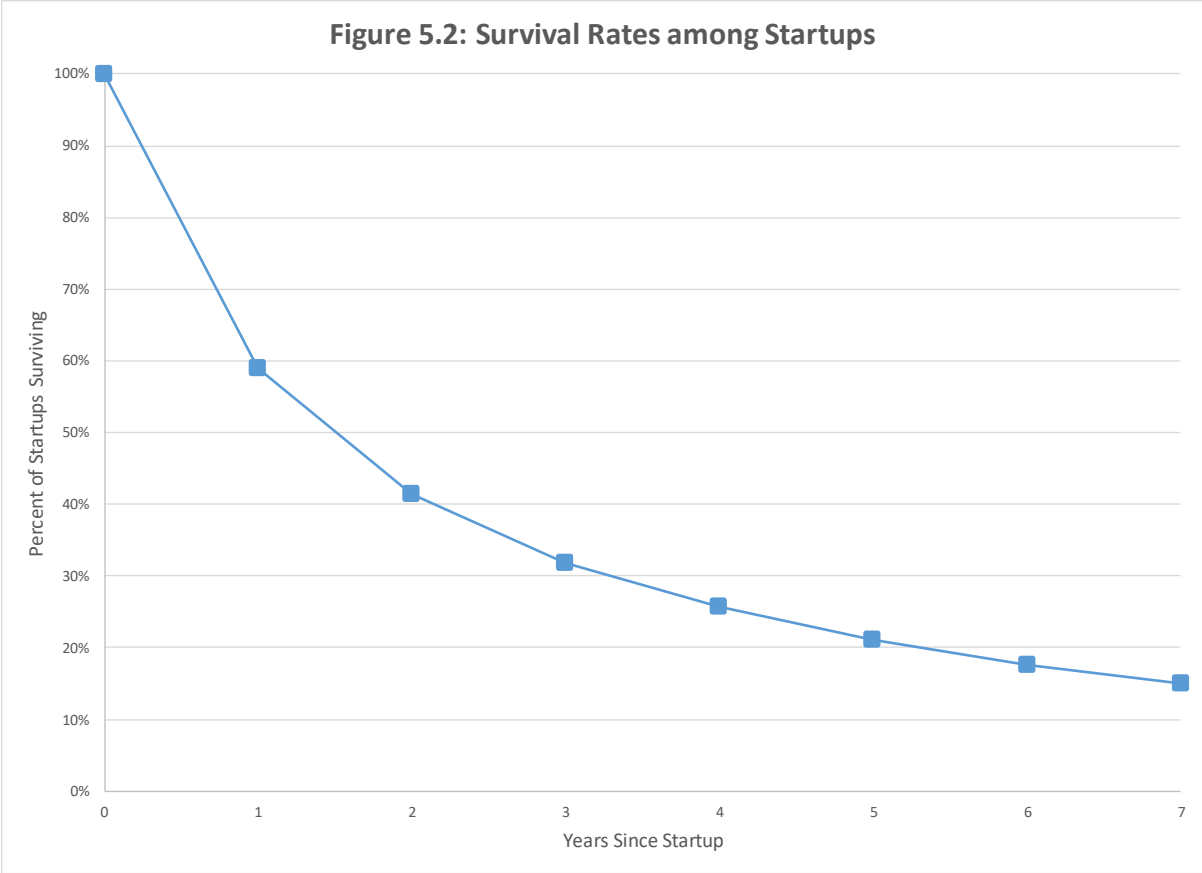


Source: Authors calculations of combined iLBD and LBD files.

Figure 5: Number of Survivors per Startup Cohort

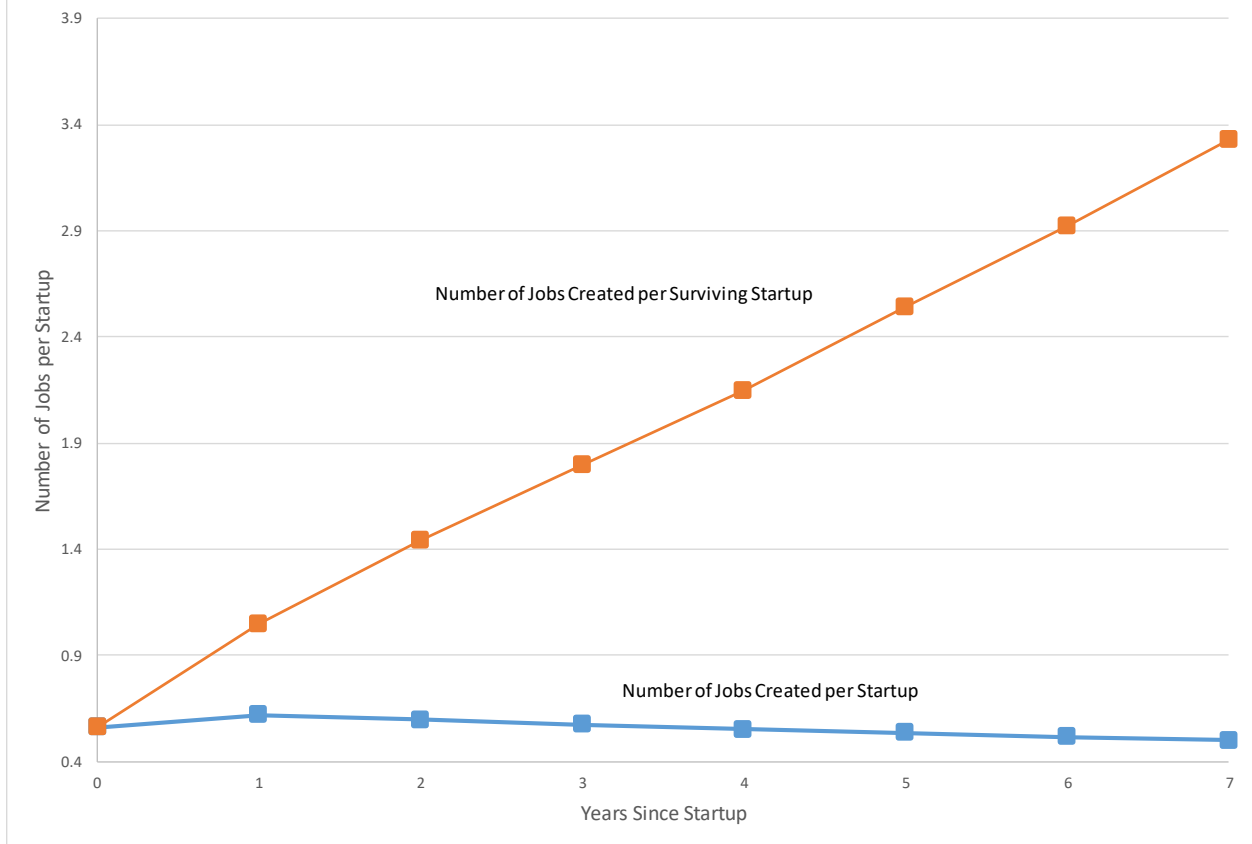


Source: Authors calculations of combined iLBD and LBD files.

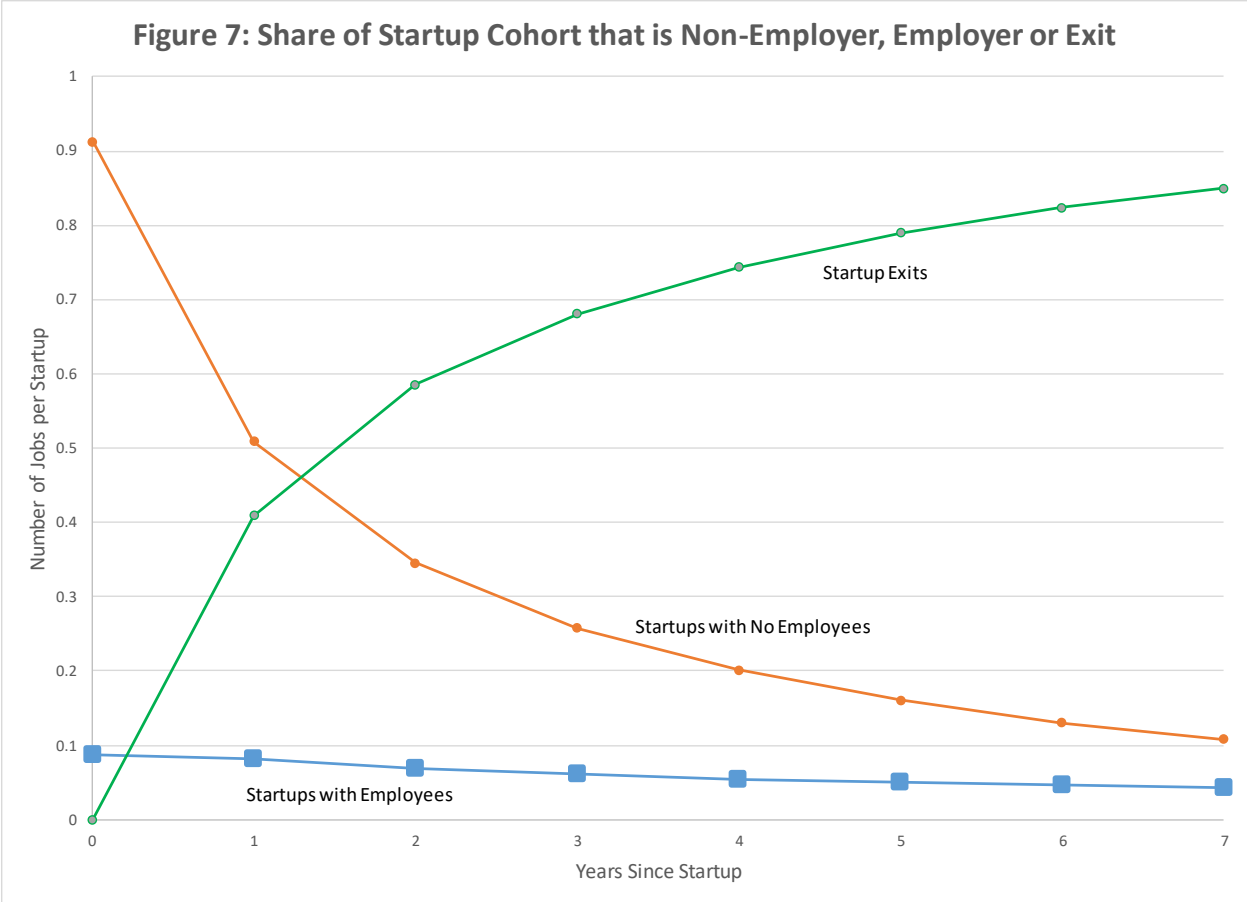


Source: Authors calculations of combined iLBD and LBD files.

Figure 6: Number of Jobs Created per Startup or Surviving Business

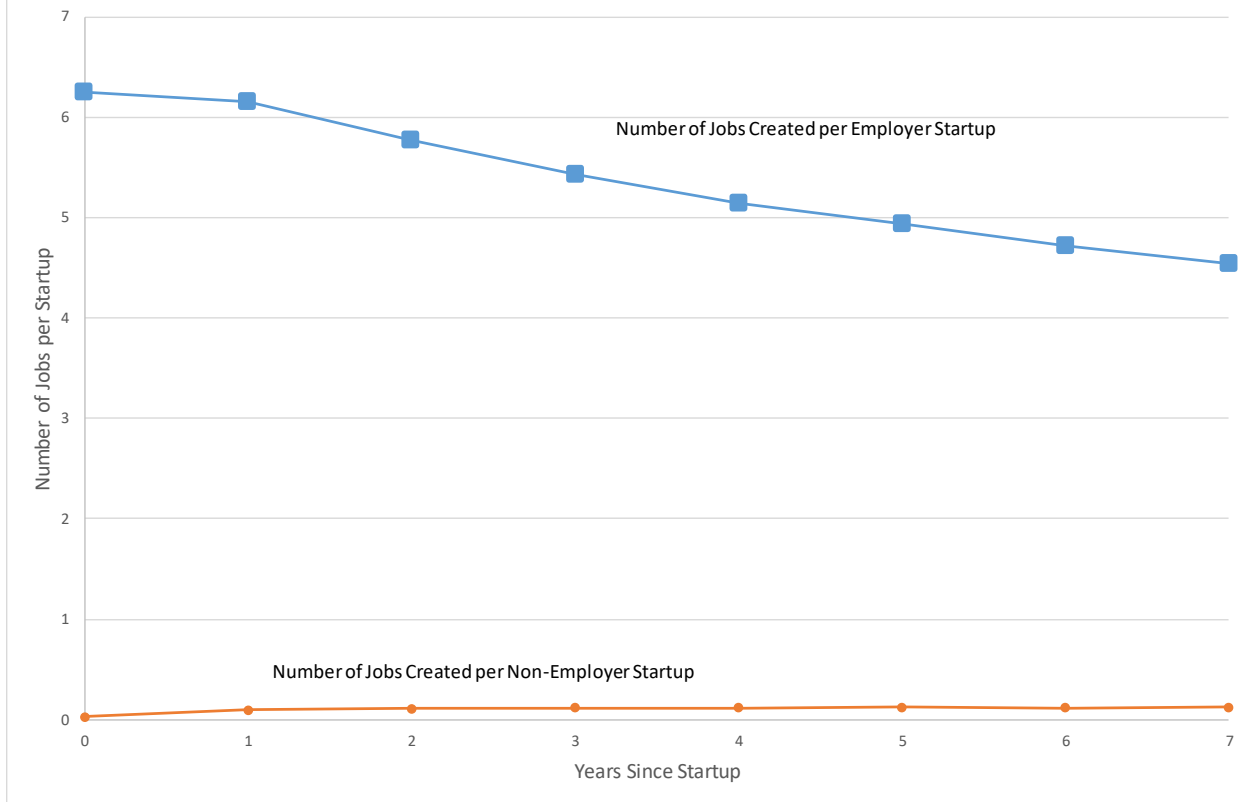


Source: Authors calculations of combined iLBD and LBD files.



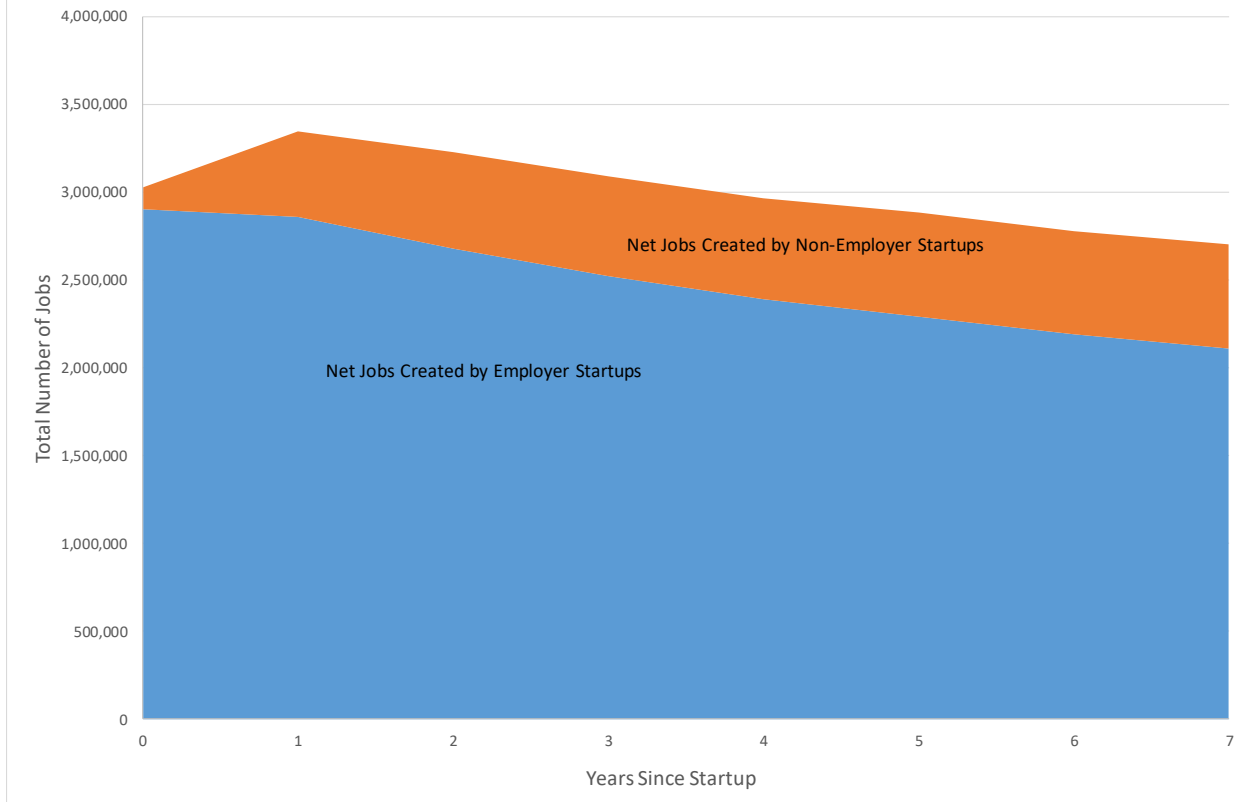
Source: Authors calculations of combined iLBD and LBD files.

Figure 8: Number of Jobs Created per Startup by Employer vs. Non-Employer



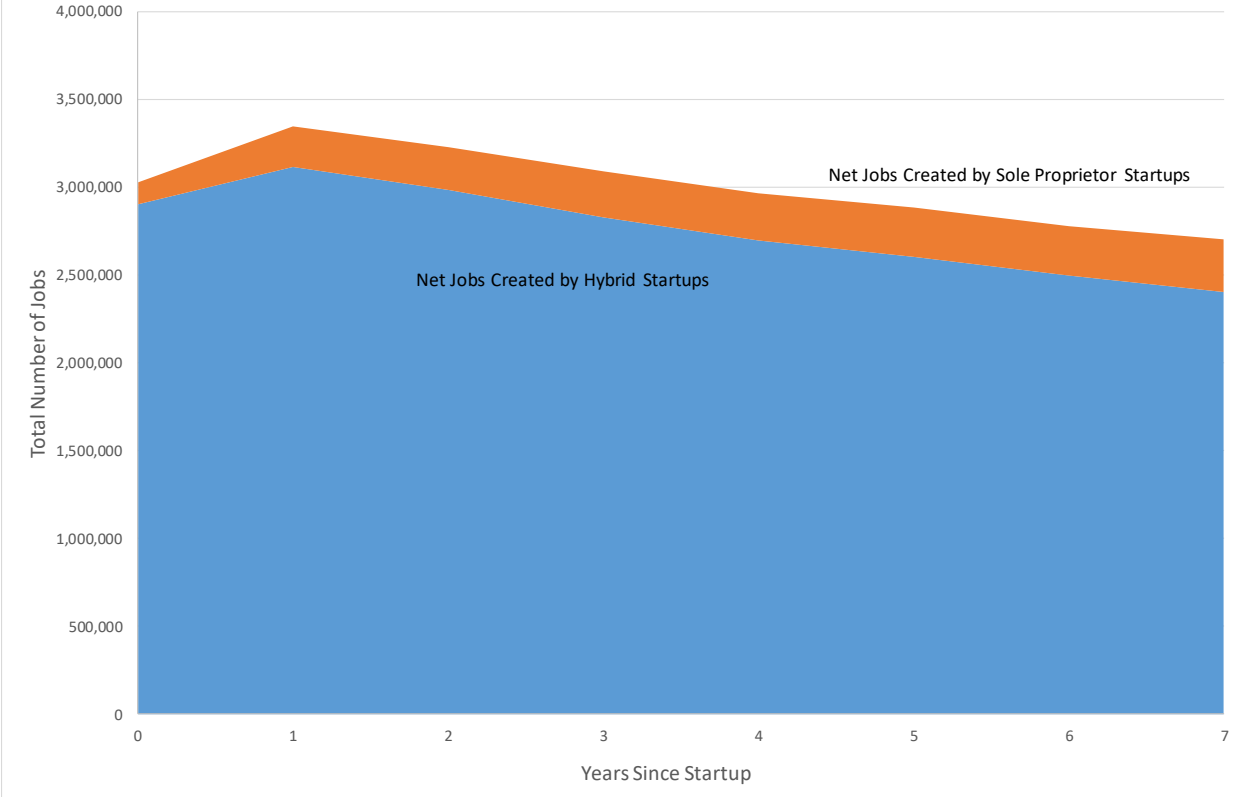
Source: Authors calculations of combined iLBD and LBD files.

Figure 9: Number of Jobs Created per Non-Employer and Employer Startup Cohort



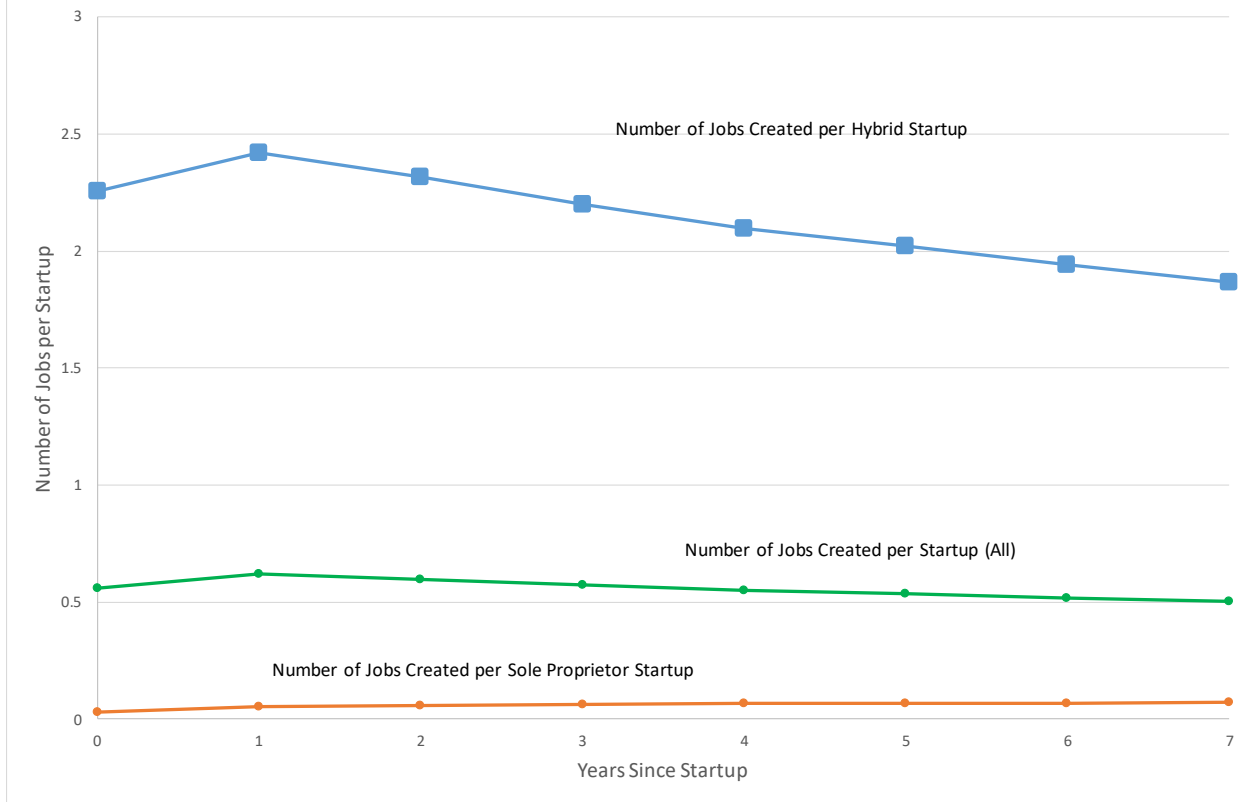
Source: Authors calculations of combined iLBD and LBD files.

Figure 10: Number of Jobs Created per Hybrid and Sole Proprietor Startup Cohort

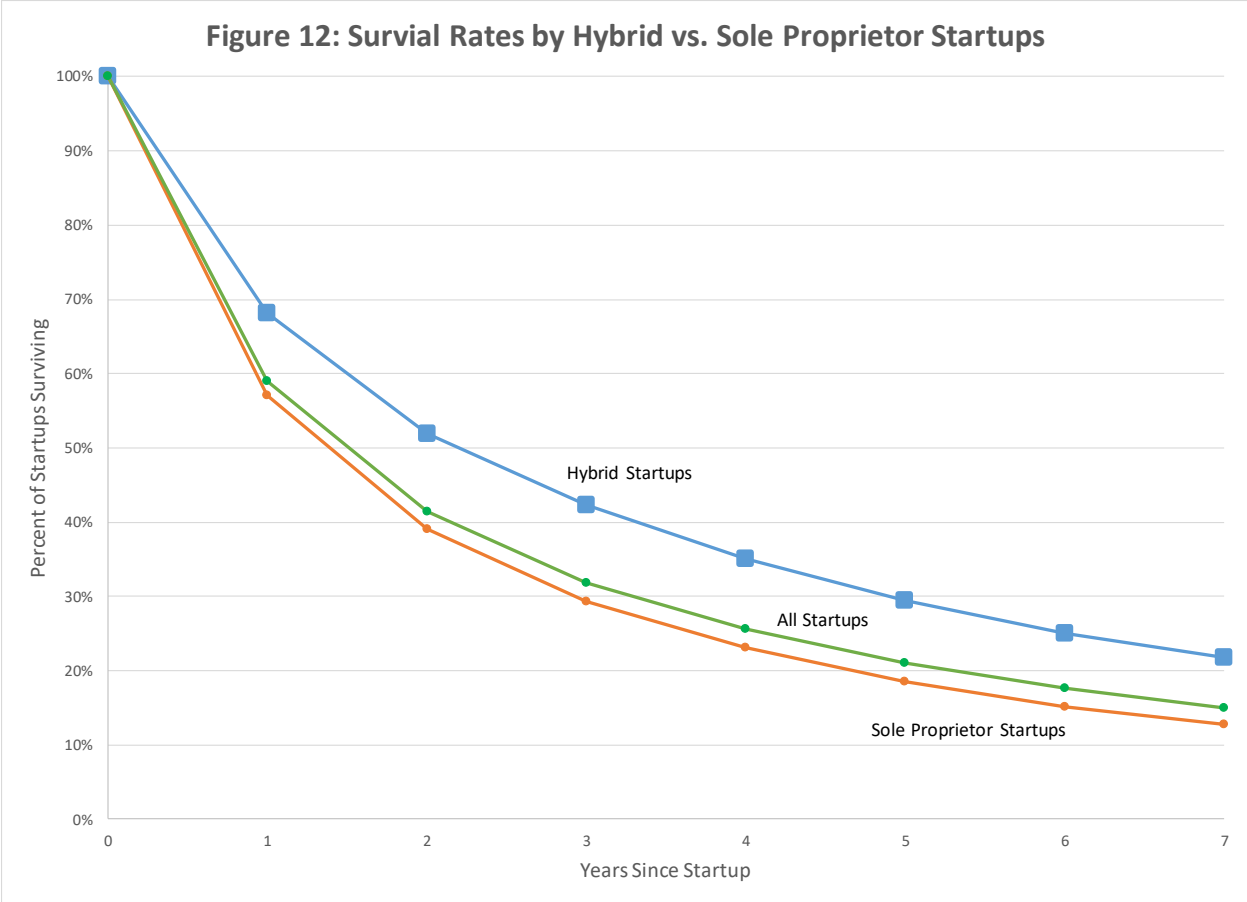


Source: Authors calculations of combined iLBD and LBD files.

Figure 11: Number of Jobs Created per Startup by Hybrid vs. Sole Proprietor



Source: Authors calculations of combined iLBD and LBD files.



Source: Authors calculations of combined iLBD and LBD files.

Table 1: Mean Number of Startups, Employment and Survival, 1995-2010

Years Since Startup	Startups	Total Employment	Average Employment	Surviving Startups	Survival Rate
0	5,392,000	3,028,000	0.56	5,392,000	100%
1	5,392,000	3,347,000	0.62	3,183,000	59%
2	5,392,000	3,228,000	0.60	2,235,000	41%
3	5,392,000	3,090,000	0.57	1,719,000	32%
4	5,392,000	2,968,000	0.55	1,383,000	26%
5	5,392,000	2,885,000	0.54	1,135,000	21%
6	5,392,000	2,780,000	0.52	950,000	18%
7	5,392,000	2,703,000	0.50	811,000	15%

Source: Authors calculations of combined iLBD and LBD files. Results are rounded for disclosure purposes.

Table 2: OLS Regression for Number of Employees among Startups, 1995-2010

Independent Variable	(1) All Startups Employees	(2) Surviving Startups Employees
1 Year Since Startup	0.0330*** (0.00321)	0.455*** (0.00508)
2 Years Since Startup	0.00628 (0.00329)	0.819*** (0.00717)
3 Years Since Startup	-0.0200*** (0.00353)	1.153*** (0.00966)
4 Years Since Startup	-0.0461*** (0.00375)	1.458*** (0.0121)
5 Years Since Startup	-0.0613*** (0.00394)	1.811*** (0.0154)
6 Years Since Startup	-0.0801*** (0.00402)	2.147*** (0.0185)
7 Years Since Startup	-0.0934*** (0.00429)	2.507*** (0.0230)
11-Agriculture, Forestry, Fishing and Hunting	-0.158*** (0.00408)	-0.229*** (0.0106)
21-Mining	0.232*** (0.0185)	0.496*** (0.0419)
22-Utilities	0.295*** (0.0473)	0.924*** (0.125)
23-Construction	0.207*** (0.00325)	0.590*** (0.00811)
31-33-Manufacturing	1.506*** (0.0254)	3.609*** (0.0603)
42-Wholesale Trade	0.652*** (0.0139)	1.565*** (0.0329)
44-45-Retail Trade	0.202*** (0.00340)	0.615*** (0.00856)
48-49-Transportation and Warehousing	0.143*** (0.0102)	0.387*** (0.0253)
51-Information	0.455*** (0.0259)	1.576*** (0.0726)
52-Finance and Insurance	0.220*** (0.00993)	0.458*** (0.0225)
53-Real Estate and Rental and Leasing	-0.0406*** (0.00315)	-0.308*** (0.00677)
54-Professional, Scientific, and Technical Services	0.145*** (0.00454)	0.355*** (0.0111)
55-Management of Companies and Enterprises	2.297*** (0.120)	5.085*** (0.271)
56-Administrative and Support and Waste Management and Remediation Services	0.531*** (0.0147)	1.709*** (0.0408)
61-Educational Services	0.202*** (0.0163)	0.643*** (0.0435)
62-Health Care and Social Assistance	0.558*** (0.00836)	1.533*** (0.0216)
71-Arts, Entertainment, and Recreation	0.0831*** (0.0105)	0.189*** (0.0252)
72-Accommodation and Food Services	2.905*** (0.0291)	6.870*** (0.0683)
Observations	304,000,000	118,570,000

Source: Combined iLBD and LBD file. Standard errors in parenthesis, clustered at the firm level. * p<0.05, ** p<0.01, *** p<0.001.

Table 3: OLS Regression for Survival Probability among Startups, 1995-2010

Independent Variable	(1)	(2)
	All Startups Survival	All Startups w/o Sole Proprietorships Survival
1 Year Since Startup	-0.3808*** (0.00008)	-0.3293*** (0.00020)
2 Years Since Startup	-0.5568*** (0.00008)	-0.5145*** (0.00021)
3 Years Since Startup	-0.6564*** (0.00008)	-0.6224*** (0.00020)
4 Years Since Startup	-0.7221*** (0.00007)	-0.7043*** (0.00019)
5 Years Since Startup	-0.7710*** (0.00007)	-0.7662*** (0.00018)
6 Years Since Startup	-0.8073*** (0.00006)	-0.8157*** (0.00017)
7 Years Since Startup	-0.8350*** (0.00006)	-0.8518*** (0.00016)
11-Agriculture, Forestry, Fishing and Hunting	-0.0452*** (0.00038)	0.00394*** (0.00088)
21-Mining	0.02038*** (0.00089)	0.07678*** (0.00172)
22-Utilities	-0.0370*** (0.00151)	0.04897*** (0.00372)
23-Construction	-0.0217*** (0.00021)	-0.0083*** (0.00073)
31-33-Manufacturing	-0.0008* (0.00038)	-0.0209*** (0.00090)
42-Wholesale Trade	0.00272*** (0.00035)	-0.0262*** (0.00081)
44-45-Retail Trade	-0.0245*** (0.00021)	-0.0291*** (0.00073)
48-49-Transportation and Warehousing	-0.0083*** (0.00029)	-0.0019* (0.00096)
51-Information	-0.0735*** (0.00034)	-0.0786*** (0.00080)
52-Finance and Insurance	0.02863*** (0.00030)	0.04892*** (0.00071)
53-Real Estate and Rental and Leasing	0.10216*** (0.00026)	0.16475*** (0.00066)
54-Professional, Scientific, and Technical Services	0.00093*** (0.00021)	0.01034*** (0.00071)
55-Management of Companies and Enterprises	0.05840*** (0.00134)	0.08301*** (0.00153)
56-Administrative and Support and Waste Management and Remediation Services	-0.0655*** (0.00022)	-0.0570*** (0.00079)
61-Educational Services	-0.0346*** (0.00040)	-0.0049** (0.00186)
62-Health Care and Social Assistance	-0.0273*** (0.00023)	-0.0134*** (0.00097)
71-Arts, Entertainment, and Recreation	0.00581*** (0.00030)	0.00018 (0.00104)
72-Accommodation and Food Services	0.00728*** (0.00037)	-0.0367*** (0.00094)
Observations	304M	74.23M

Source: Combined iLBD and LBD file. Standard errors in parenthesis, clustered at the firm level. * p<0.05, ** p<0.01, *** p<0.001.

Table 4: Employment Size Distribution among Startups, 1995-2010

Years Since Startup	Any Employees	1-4	5-9	10-19	20-49	50-99	100-249	250-499	500+
0	9.4%	86.0%	8.6%	3.3%	1.5%	0.3%	0.1%	0.0%	0.0%
1	8.4%	67.2%	18.3%	8.5%	4.3%	1.1%	0.4%	0.1%	0.1%
2	7.2%	63.0%	19.9%	9.9%	5.2%	1.3%	0.6%	0.1%	0.1%
3	6.4%	60.5%	20.7%	10.7%	5.7%	1.5%	0.6%	0.1%	0.1%
4	5.7%	58.9%	21.2%	11.3%	6.1%	1.6%	0.7%	0.2%	0.1%
5	5.2%	57.6%	21.4%	11.8%	6.4%	1.7%	0.8%	0.2%	0.1%
6	4.7%	57.8%	19.6%	11.9%	7.3%	2.0%	1.0%	0.2%	0.2%
7	4.4%	57.3%	19.7%	11.9%	7.5%	2.2%	1.0%	0.2%	0.2%

Source: Authors calculations based on combined LBD and iLBD file

Table 5: OLS Regression for Number of Employees among Restricted Types of Startups, 1995-2010

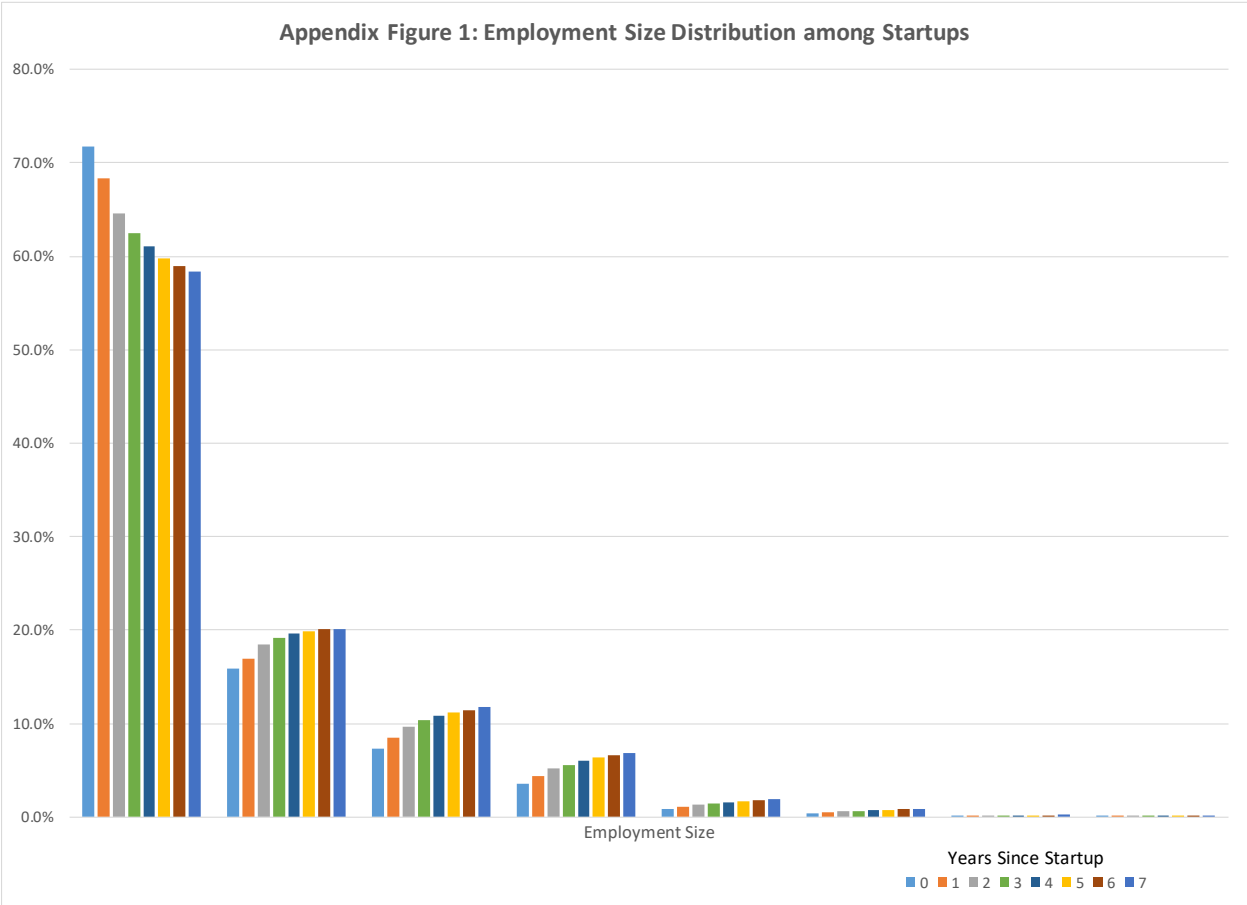
Independent Variable	(1)	(2)
	All Startups w/o Sole Proprietorships Employees	Surviving Startups w/o Sole Proprietorships Employees
1 Year Since Startup	0.289*** (0.00396)	0.529*** (0.00615)
2 Years Since Startup	0.347*** (0.00351)	0.860*** (0.00810)
3 Years Since Startup	0.353*** (0.00312)	1.120*** (0.00965)
4 Years Since Startup	0.354*** (0.00341)	1.385*** (0.0128)
5 Years Since Startup	0.351*** (0.00345)	1.695*** (0.0159)
6 Years Since Startup	0.350*** (0.00430)	2.074*** (0.0240)
7 Years Since Startup	0.340*** (0.00448)	2.437*** (0.0303)
11-Agriculture, Forestry, Fishing and Hunting	-0.184*** (0.00686)	-0.419*** (0.0174)
21-Mining	-0.0681*** (0.0127)	-0.309*** (0.0280)
22-Utilities	0.0985 (0.0516)	0.103 (0.115)
23-Construction	0.111*** (0.00894)	0.333*** (0.0230)
31-33-Manufacturing	0.404*** (0.0168)	1.147*** (0.0436)
42-Wholesale Trade	0.0756*** (0.00957)	0.296*** (0.0251)
44-45-Retail Trade	0.0895*** (0.00801)	0.346*** (0.0210)
48-49-Transportation and Warehousing	0.0702*** (0.0116)	0.193*** (0.0293)
51-Information	0.107*** (0.0125)	0.587*** (0.0349)
52-Finance and Insurance	-0.122*** (0.00692)	-0.336*** (0.0172)
53-Real Estate and Rental and Leasing	-0.175*** (0.00626)	-0.667*** (0.0159)
54-Professional, Scientific, and Technical Services	0.0545*** (0.00895)	0.129*** (0.0228)
55-Management of Companies and Enterprises	0.0301 (0.0588)	-0.0699 (0.135)
56-Administrative and Support and Waste Management and Remediation Services	0.459*** (0.0244)	1.466*** (0.0677)
61-Educational Services	0.175*** (0.0242)	0.464*** (0.0611)
62-Health Care and Social Assistance	0.622*** (0.0197)	1.660*** (0.0506)
71-Arts, Entertainment, and Recreation	0.0997*** (0.0233)	0.274*** (0.0596)
72-Accommodation and Food Services	0.983*** (0.0243)	2.862*** (0.0660)
Observations	74.23M	34.6M

Source: Combined iLBD and LBD file. Standard errors in parenthesis, clustered at the firm level. * p<0.05, ** p<0.01, *** p<0.001.

Table 6: Range of Measures for Employment per Entrepreneur and Survival Rates

Years since Startup	Employment per Entrepreneur		Survival Rates	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound
0	0.56	2.25	100%	100%
1	0.62	2.42	59%	68%
2	0.6	2.32	41%	52%
3	0.57	2.2	32%	42%
4	0.55	2.1	26%	35%
5	0.53	2.02	21%	29%
6	0.52	1.94	18%	25%
7	0.5	1.87	15%	22%

Source: Author calculations based on combined LBD and iLBD database



Source: Authors calculations of combined iLBD and LBD files.

Appendix Table 1: Employer and Non-Employer Tax Units

Year	Total Tax Units	Non Employer Tax Units	Employer Tax Units	Number of Employer Establishments	Percent Non-Employer
1997	20,190,000	15,440,000	4,750,000	6,040,000	76
1998	20,500,000	15,710,000	4,800,000	6,110,000	77
1999	20,980,000	16,150,000	4,820,000	6,170,000	77
2000	21,370,000	16,530,000	4,840,000	6,220,000	77
2001	21,860,000	16,980,000	4,880,000	6,310,000	78
2002	22,550,000	17,650,000	4,910,000	6,350,000	78
2003	23,610,000	18,650,000	4,960,000	6,420,000	79
2004	24,560,000	19,520,000	5,040,000	6,500,000	79
2005	25,530,000	20,390,000	5,140,000	6,630,000	80
2006	25,950,000	20,770,000	5,180,000	6,740,000	80
2007	26,950,000	21,710,000	5,240,000	6,840,000	81
2008	26,550,000	21,350,000	5,200,000	6,830,000	80
2009	26,720,000	21,700,000	5,030,000	6,650,000	81
2010	27,060,000	22,110,000	4,950,000	6,580,000	82
2011	27,400,000	22,490,000	4,910,000	6,550,000	82
2012	27,720,000	22,740,000	4,980,000	6,630,000	82
2013	28,030,000	23,010,000	5,020,000	6,670,000	82
2014	28,890,000	23,840,000	5,060,000	6,720,000	82

Source: U.S. Census Bureau Business Dynamics Statistics and Non-Employer Statistics. Results have been rounded for disclosure purposes

Appendix Table 2: Average Employment of Startups by Industry and Years since Startup (All Startups)

Sector	Number of Startups	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7
		Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.
11-Agriculture, Forestry, Fishing and Hunting	680,000	0.11	0.12	0.11	0.11	0.09	0.08	0.08	0.07
21-Mining	130,000	0.52	0.54	0.50	0.50	0.44	0.44	0.47	0.45
22-Utilities	30,000	0.69	0.61	0.54	0.53	0.56	0.52	0.50	0.43
23-Construction	4,070,000	0.50	0.51	0.49	0.47	0.45	0.44	0.42	0.40
31-33-Manufacturing	800,000	1.83	1.95	1.87	1.86	1.74	1.69	1.57	1.57
42-Wholesale Trade	970,000	0.92	1.01	0.97	0.90	0.89	0.88	0.86	0.83
44-45-Retail Trade	4,060,000	0.53	0.54	0.50	0.46	0.43	0.42	0.39	0.37
48-49-Transportation and Warehousing	1,480,000	0.42	0.45	0.43	0.40	0.38	0.38	0.36	0.35
51-Information	840,000	0.59	0.82	0.82	0.77	0.70	0.69	0.65	0.63
52-Finance and Insurance	1,390,000	0.45	0.48	0.47	0.47	0.46	0.48	0.48	0.49
53-Real Estate and Rental and Leasing	2,300,000	0.23	0.25	0.23	0.21	0.20	0.20	0.19	0.18
54-Professional, Scientific, and Technical Services	4,280,000	0.42	0.45	0.43	0.40	0.38	0.37	0.36	0.36
55-Management of Companies and Enterprises	30,000	5.31	3.85	2.71	2.27	2.26	1.61	1.80	1.75
56-Administrative and Support and Waste Management and Remediation Services	3,230,000	0.69	0.82	0.85	0.84	0.81	0.77	0.75	0.75
61-Educational Services	600,000	0.42	0.43	0.44	0.44	0.46	0.44	0.47	0.48
62-Health Care and Social Assistance	2,880,000	0.73	0.83	0.83	0.83	0.81	0.82	0.81	0.81
71-Arts, Entertainment, and Recreation	1,280,000	0.35	0.36	0.36	0.35	0.32	0.32	0.31	0.30
72-Accommodation and Food Services	860,000	4.10	3.78	3.38	3.14	2.95	2.79	2.65	2.52
81-Other Services (except Public Administration)	4,020,000	0.29	0.29	0.27	0.25	0.25	0.23	0.23	0.21
Total Observations	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M

Source: Authors calculations based on combined LBD and iLBD databases.

Appendix Table 3: Average Survival Rate of Startups by Industry and Years since Startup (All Startups)

Sector	Number of Startups	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7
		Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival
11-Agriculture, Forestry, Fishing and Hunting	680,000	1.00	0.60	0.41	0.31	0.24	0.19	0.14	0.11
21-Mining	130,000	1.00	0.65	0.49	0.39	0.32	0.26	0.22	0.19
22-Utilities	30,000	1.00	0.60	0.42	0.31	0.24	0.19	0.16	0.13
23-Construction	4,070,000	1.00	0.59	0.42	0.33	0.27	0.22	0.19	0.16
31-33-Manufacturing	800,000	1.00	0.63	0.46	0.35	0.29	0.24	0.21	0.18
42-Wholesale Trade	970,000	1.00	0.64	0.47	0.36	0.29	0.24	0.20	0.18
44-45-Retail Trade	4,060,000	1.00	0.62	0.43	0.33	0.26	0.21	0.17	0.14
48-49-Transportation and Warehousing	1,480,000	1.00	0.62	0.44	0.34	0.28	0.23	0.20	0.17
51-Information	840,000	1.00	0.58	0.37	0.25	0.19	0.15	0.12	0.10
52-Finance and Insurance	1,390,000	1.00	0.69	0.51	0.40	0.32	0.26	0.21	0.18
53-Real Estate and Rental and Leasing	2,300,000	1.00	0.74	0.59	0.49	0.42	0.35	0.30	0.25
54-Professional, Scientific, and Technical Services	4,280,000	1.00	0.63	0.46	0.36	0.29	0.24	0.20	0.17
55-Management of Companies and Enterprises	30,000	1.00	0.75	0.59	0.49	0.38	0.27	0.18	0.12
56-Administrative and Support and Waste Management and Remediation Services	3,230,000	1.00	0.56	0.37	0.26	0.21	0.17	0.15	0.13
61-Educational Services	600,000	1.00	0.58	0.40	0.30	0.25	0.20	0.17	0.15
62-Health Care and Social Assistance	2,880,000	1.00	0.60	0.41	0.31	0.25	0.21	0.18	0.15
71-Arts, Entertainment, and Recreation	1,280,000	1.00	0.63	0.46	0.37	0.30	0.24	0.20	0.17
72-Accommodation and Food Services	860,000	1.00	0.62	0.46	0.36	0.30	0.26	0.22	0.19
81-Other Services (except Public Administration)	4,020,000	1.00	0.61	0.45	0.35	0.29	0.24	0.21	0.18
Total Observations	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M	36.47M

Source: Authors calculations based on combined LBD and iLBD databases.

Appendix Table 4: Average Employment of Startups by Industry and Years since Startup (Excluding Sole-Proprietorship, Non-Employer Startups)

Sector	Number of Startups	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7
		Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.	Avg. Emp.
11-Agriculture, Forestry, Fishing and Hunting	190,000	0.39	0.38	0.35	0.32	0.28	0.25	0.24	0.22
21-Mining	50,000	1.44	1.45	1.34	1.28	1.08	1.04	1.11	1.05
22-Utilities	10,000	2.35	2.08	1.85	1.78	1.82	1.65	1.44	1.24
23-Construction	930,000	2.15	2.16	2.06	1.95	1.87	1.82	1.75	1.68
31-33-Manufacturing	340,000	4.23	4.44	4.18	3.92	3.69	3.48	3.26	3.13
42-Wholesale Trade	460,000	1.92	2.03	1.93	1.80	1.76	1.73	1.70	1.61
44-45-Retail Trade	880,000	2.43	2.39	2.20	2.04	1.90	1.79	1.68	1.58
48-49-Transportation and Warehousing	280,000	2.14	2.22	2.14	1.99	1.89	1.86	1.73	1.61
51-Information	320,000	1.51	2.04	2.08	2.05	1.89	1.83	1.72	1.61
52-Finance and Insurance	690,000	0.89	0.94	0.92	0.90	0.89	0.89	0.87	0.85
53-Real Estate and Rental and Leasing	1,330,000	0.40	0.41	0.38	0.35	0.33	0.31	0.30	0.28
54-Professional, Scientific, and Technical Services	910,000	1.93	1.98	1.91	1.79	1.70	1.66	1.59	1.57
55-Management of Companies and Enterprises	30,000	5.33	3.81	2.53	2.02	1.93	1.41	1.51	1.47
56-Administrative and Support and Waste Management and Remediation Services	520,000	4.17	4.94	5.11	5.02	4.82	4.61	4.47	4.37
61-Educational Services	70,000	3.83	3.82	3.79	3.90	4.11	3.90	4.06	4.04
62-Health Care and Social Assistance	420,000	4.86	5.30	5.39	5.31	5.18	5.24	5.18	5.11
71-Arts, Entertainment, and Recreation	170,000	2.59	2.58	2.50	2.37	2.31	2.25	2.10	2.07
72-Accommodation and Food Services	480,000	7.26	6.56	5.97	5.54	5.19	4.88	4.63	4.36
81-Other Services (except Public Administration)	550,000	2.06	1.97	1.84	1.72	1.63	1.57	1.49	1.45
Total Observations	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M

Source: Authors calculations based on combined LBD and iLBD databases.

Appendix Table 5: Average Survival Rate of Startups by Industry and Years since Startup (Excluding Sole-Proprietorship, Non-Employer Startups)

Sector	Number of Startups	Year 0	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7
		Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival	Avg. Survival
11-Agriculture, Forestry, Fishing and Hunting	190,000	1.00	0.68	0.48	0.38	0.29	0.21	0.15	0.11
21-Mining	50,000	1.00	0.73	0.57	0.47	0.38	0.31	0.26	0.22
22-Utilities	10,000	1.00	0.69	0.55	0.45	0.38	0.32	0.26	0.21
23-Construction	930,000	1.00	0.68	0.53	0.43	0.36	0.31	0.27	0.24
31-33-Manufacturing	340,000	1.00	0.69	0.53	0.43	0.36	0.31	0.27	0.24
42-Wholesale Trade	460,000	1.00	0.68	0.51	0.41	0.34	0.29	0.25	0.22
44-45-Retail Trade	880,000	1.00	0.68	0.51	0.42	0.35	0.30	0.26	0.23
48-49-Transportation and Warehousing	280,000	1.00	0.67	0.50	0.40	0.33	0.28	0.24	0.21
51-Information	320,000	1.00	0.62	0.40	0.27	0.21	0.17	0.14	0.11
52-Finance and Insurance	690,000	1.00	0.75	0.57	0.46	0.35	0.28	0.22	0.18
53-Real Estate and Rental and Leasing	1,330,000	1.00	0.80	0.65	0.56	0.47	0.40	0.34	0.28
54-Professional, Scientific, and Technical Services	910,000	1.00	0.70	0.54	0.45	0.37	0.32	0.28	0.25
55-Management of Companies and Enterprises	30,000	1.00	0.75	0.59	0.49	0.37	0.27	0.18	0.12
56-Administrative and Support and Waste Management and Remediation Services	520,000	1.00	0.66	0.48	0.38	0.32	0.27	0.24	0.21
61-Educational Services	70,000	1.00	0.71	0.56	0.47	0.41	0.36	0.33	0.30
62-Health Care and Social Assistance	420,000	1.00	0.72	0.59	0.51	0.45	0.41	0.38	0.35
71-Arts, Entertainment, and Recreation	170,000	1.00	0.69	0.51	0.40	0.33	0.27	0.23	0.20
72-Accommodation and Food Services	480,000	1.00	0.67	0.52	0.43	0.37	0.32	0.28	0.25
81-Other Services (except Public Administration)	550,000	1.00	0.70	0.56	0.47	0.40	0.35	0.31	0.28
Total Observations	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M	8.8M

Source: Authors calculations based on combined LBD and iLBD databases.