EMPLOYMENT EFFECTS OF FINANCIAL CONSTRAINTS DURING THE GREAT RECESSION

Michael Siemer*

Abstract—Employment declined substantially during the 2007–2009 recession, especially in small and young firms. Using confidential firm-level data of the universe of firms and a difference-in-differences methodology, this paper estimates that financial constraints reduced employment growth by 4 to 8 percentage points in small firms relative to large firms and by 7 to 9 percentage points in young relative to old firms. I find that the effect of financial constraints on small firms is driven to a large extent by young firms. I then document that financial constraints affected employment growth in small and young firms strongly through the entry and exit of firms.

1. Introduction

The 2007–2009 recession and the subsequent economic recovery in the United States differed from most other historical business cycles in several ways. First, the Great Recession exhibited a large reduction in employment, which was concentrated in small and young firms: employment declined by almost 8% in small firms and 16% in young firms. Second, the number of firms showed an unprecedented 5% decline through 2010, which was driven to a large extent by a decline in the number of young firms. Third, credit conditions were tight, and the 2007–2009 recession is one of only two recessions since the late 1970s during which aggregate commercial bank lending declined.1

In light of these unique characteristics of the Great Recession, this paper examines if financial constraints had a significant effect on employment growth in small versus large and young versus old firms. This paper thus contributes to the growing empirical literature on the macroeconomic implications of financial constraints. The literature has mostly focused on the effect of financial constraints on small and large firms (Gertler & Gilchrist, 1994; Chodorow-Reich, 2014; Duygan-Bump, Levkov, & Montoriol-Garriga, 2015). The key contribution of this paper is to show that during the 2007–2009 recession, financial constraints affected young firms most strongly and that the differential effect of financial constraints on small versus large firms was largely driven by the effect of financial constraints on young firms, which tend to be small. Young firms lack established lending relationships and by definition have a short track record of performance and creditworthiness. Thus, they are more likely to be exposed to changes in financial conditions. While small firms account for 30% of aggregate employment and historically received significant attention from policymakers and researchers, this paper shows that business conditions for young firms, some of which could be the next generation’s Amazon, Google, or Tesla, should be considered seriously.

I use confidential firm-level employment data from the Quarterly Census of Employment and Wages (QCEW) Longitudinal Database (LDB) from the Bureau of Labor Statistics (BLS). Unlike the existing empirical literature—which typically ignores 95% of firms that have fewer than fifty employees and often excludes start-ups or lack information on firm age entirely (Benmelech, Bergman, & Seru, 2011; Chodorow-Reich, 2014)—this study examines employment growth of the full universe of firms during the 2007–2009 recession in the United States. The results of this paper imply that external financial constraints accounted for a reduction in employment growth of 4 to 8 percentage points for small firms relative to large firms and 7 to 10 percentage points for young relative to old firms during the 2007–2009 period. I show that this finding for small firms is driven primarily by young firms and document the importance of entry and exit margins for the differential effect of external financial dependence (EFD). It is important to understand the factors driving the employment decline in small and young firms because a decline in young firms and potential start-ups may have significant implications for economic growth in subsequent years (Buera & Moll, 2015; Bassetto, Cagetti, & De Nardi, 2015; Clementi et al., 2015; Gourio, Messer, & Siemer, 2016; Clementi & Palazzo, 2016).

I construct an EFD measure on the sectoral level from Compustat data, based on work by Rajan and Zingales (1998), Kaplan and Zingales (2000), and Cetorelli and Strahan (2006). This measure captures the external financing demand of a given sector by comparing firm cash flows with capital expenditures over multiple years, allowing for the construction of composite sectors of high and low EFD. This paper employs a difference-in-differences (DD) identification strategy, which compares small and large firms in low-EFD sectors with small and large firms in high-EFD sectors. The difference between small firms in low-EFD sectors and small firms in high-EFD sectors identifies a financing constraint effect combined with a high-EFD industry effect. The remaining potential identification issue is that high-EFD industries may be more (or less) sensitive to changes in the business cycle. However, if the high-EFD effect is constant across firm size, then further differencing by the difference between large firms in low-EFD and high-EFD industries removes the high-EFD industry effect. I find that financial

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1 The other was the 1991 recession in the aftermath of the savings and loan crisis (Contessi & Francis, 2011).

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constraints reduced employment growth in small firms relative to large firms by 4 percentage points during the financial crisis. However, if there are permanent differences in growth rates between small and large firms across high- and low-EFD industries, a further difference in the same comparison over a time period without a financial shock would identify the tight credit effect. A difference-in-differences-in-differences (DDD) estimator suggests that financial constraints reduced employment growth by 8 percentage points in small firms relative to large firms during the 2007–2009 recession. This finding supports the notion that small firms are more affected by credit constraints than large firms.

This paper further contributes to the literature by moving beyond the small-versus-large comparison and showing an analogously constructed estimate for the effect of financial constraints on young relative to old firms. A DD estimator for young versus old firms, computed analogous to the large versus small DD estimator, implies that financial constraints reduced employment growth in young firms by 7 percentage points relative to old firms from 2007 to 2009. The corresponding DDD estimator pegs the effect at about 9 percentage points. I show that the effect of financial constraints on small firms is driven by young firms, which tend to be small. This paper also shows that the effect of financial constraints on small and young firms works strongly through the extensive margin, that is, the entry and exit of firms. Finally, I document the aggregate implications of my findings.

This paper is related to the literature that examines the determinants of the employment decline from 2007 to 2009. The most closely related paper in terms of empirical methodology is Duygan-Bump et al. (2015), which examines the effect of financial constraints on unemployment outcomes for employees of small and large firms. The authors use Compustat data to derive financial constraint measures, as this paper does, and they also rely on a similar identification strategy. The authors find that workers in small firms in high externally financial dependent sectors are more likely to become unemployed. However, there are important differences between that paper and this one. First, the authors rely on CPS data, which means they do not actually measure employment at firms affected by financial constraints. Second, the authors are not able to examine the role of firm age. Although young firms tend to be small, the key finding of my paper is that young firms in particular were most affected by financial constraints, which may have very different policy implications. Finally, there are certain scenarios under which the estimates of Duygan-Bump et al. (2015) would not be able to differentiate out the effects of aggregate demand shocks. If, for some reason, small firms in sectors of high external financial dependence were disproportionately located in counties with larger house price declines, the authors’ estimator would assign a larger effect of financial constraints to small firms even though the employment effect could be entirely driven by aggregate demand. This paper, in contrast, controls for house price changes as well as many other county and industry observables or includes firm location (county) × industry fixed effects to capture aggregate demand effects more generally.

Benmelech et al. (2011) examine the effect of financing constraints on employment using financial and employment measures from Compustat. However, they limit their analysis to large firms with more than 500 employees. In a complementary paper to this one, Chodorow-Reich (2014) provides evidence, using syndicated loan data, that lender health matters for employment outcomes in small- and medium-sized publicly traded firms.

Other recent work on financial constraints and employment related to this paper include Schmalz, Sraer, and Thesmar (2017), Fairlie and Krashinsky (2012), and Adelino, Schoar, and Severino (2015). Schmalz et al. (2017) show, using French data, that collateral constraints inhibit firm entry and postentry growth. Adelino et al. (2015) emphasize the importance of the collateral channel and show that areas with greater increases in house prices (before 2007) experienced larger increases in employment. Fairlie and Krashinsky (2012) also emphasize the role of housing collateral for entry into self-employment.


In this section, I review stylized facts on the evolution of the firm age distribution and the firm size distribution during the financial crisis of 2007 to 2009. I use annual Business Dynamics Statistics (BDS) data from the Census Bureau.

Figure 1a, shows the number of entering and exiting firms in the data since 1985. Before the 2007–2009 financial crisis, the economy saw an increase in the number of firms entering the economy, followed by a sharp decline to historically low levels. Entry of firms fell by more than 25% between 2006 and 2010 and has essentially stayed flat since then. Meanwhile the United States experienced an increase in firm exit both before and during the crisis. The rise in firm exit, however, is somewhat larger than the decline in firm entry. Figure 1b shows that the total number of firms declined during the financial crisis as the number of exiting firms is larger than the number of entering firms. The cumulative decline in the number of firms is substantial—about 5%.

Figure 1c, displays the last decade of data on the number of firms by firm age. Naturally, there are fewer firms in the older groups than in the younger ones, as some firms exit over time. Moreover, the figure shows a 25% decline in start-ups (firms less than one year old) between 2006 and 2010. On average, start-ups account for less than 3% of aggregate employment; however, as they age, each generation gains more importance for aggregate employment. The decline in the number of start-ups during the recession moves through the age distribution as the number of two-, three-, and four-year-old firms starts to decline in subsequent years. Finally, for firms older than five years, there is no substantial decline after 2007. Figure 1d, shows firm exit by firm age. Unsurprisingly perhaps, more
young tend to close shop, on average, than old firms. At the beginning of the recession, we see a rise in firm exit for some of the younger cohorts, followed by a decline toward the end of the recession.

So far I have considered only the number of firms, but another important dimension to consider is aggregate employment. Table 1A, shows the evolution of employment during the financial crisis by firm age. Historically, a great deal of research on financial constraint has focused on firm size rather than age (Gertler & Gilchrist, 1994). Table 1B compares the evolution of employment by firm age with that of firm size. The first and second columns show that in 2007, 57% of firms were younger than ten years old but accounted for less than 25% of employment. However, young firms may be more important in aggregate than these numbers suggest because they may grow into large firms that have a large importance for the future macroeconomy. While less than 1% of firms have more than 500 employees, they account for almost 50% of aggregate employment. Small firms (those with fewer than 50 employees) are also important for the macroeconomy; 95% of firms are small, and they account for 30% of aggregate employment.

The third column in table 1 shows that the number of young firms (and small- and medium-sized firms) fell significantly more than the number of old (large) firms between 2007 and 2009.2 And the fourth column shows that small and young firms reduced employment during the Great Recession even more than what the pure reduction in the number of such firms would suggest.

The Great Recession originated in the financial sector of the United States. It is therefore important to examine the

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2 The table, as inherited from the underlying source data, does not take into account the composition bias; medium-sized firms that reduced employment in 2007 might be classified as small firms in 2009. The classification bias thus would lead the data to understate the true relative decline in the number of small firms.
extent to which financial constraints can explain the evolution of employment and the particularly large declines in employment in young and small firms during this period. I study the importance of financial constraints for firm employment growth in the next section.

III. Financial Constraints and Employment Growth: Empirical Evidence

In this section, I examine the importance of financial constraints during the Great Recession using firm-level employment data and sectoral financial constraint measures. I provide evidence on the effect of financial constraints from 2007 to 2009 on the universe of firms in the United States using confidential microdata from the BLS. I merge all establishments of each firm in the data and construct employment at the firm level, as financial constraints are typically present at the firm level rather than the establishment level. I combine these data with sectoral financial constraint measures from Compustat to examine the role of credit constraints in employment growth. By constructing a sector-level EFD measure, I can use all the firms in the BLS data.

A. Data

This section briefly describes the data set and construction of the EFD measure.

Employment data are sourced from the LDB of the QCEW and are available for all establishments in the United States since 1990. For each establishment, the LDB data provide information on employment, total wage bill, location (county and state), sector, first year of nonzero employment, and employer identification number (EIN). Each firm in the data set has an EIN. I merge all establishments with the same EIN to construct a firm. Establishments sharing one EIN have a joint tax liability; however, some larger corporations have multiple EINs, and economic control can thus extend beyond a single EIN. I follow Chodorow-Reich (2014) and exclude all firms in the real estate and financial sectors. I also remove public administration and professional employer organizations. Because firms can have establishments in different sectors or locations, I assign to each firm the sector or location in which it has the largest share of employees. About 95% of firms in the data set are single-establishment firms, with the remainder of firms having two or more establishments.

I follow Davis, Haltiwanger, and Schuh (1996), Haltiwanger, Jarmin, and Miranda (2013), and Moscarini and Postel-Vinay (2012) in defining firm-level employment growth. In particular, the growth rate (henceforth called the DHS growth rate) of employment nt at firm i in sector j in state s between year t and t − k is

\[ g_{ijst} = \frac{n_{ijst} - n_{ijst-k}}{n_{ijst-k}} \]

where \( n_{ijst-k} = \alpha n_{ijst} + (1 - \alpha)n_{ijst-k} \). A value commonly chosen for \( \alpha \) is 1/2. This definition of the growth rate has several advantages (see Moscarini & Postel-Vinay, 2012). First, the measure is symmetric for positive and negative employment changes. Second, this growth rate is well defined for entrants, and exits. For entrants, it takes the value 2, and for exits it takes the value −2. More generally, \( \% \Delta n_{ijst} \in [-2, 2] \).

The BLS employment data do not contain any financial information for the firms. Therefore, Compustat data are used to construct credit constraint measures at the sector level. I resort to sectoral financial dependence measures to exploit employment information for all firms in the firm universe rather than the smaller subset of publicly traded firms for which there are financial data available in Compustat. I construct the external financial dependence measure from financial information following the methodology in Rajan and Zingales (1998), Kaplan and Zingales (2000), and Cetorelli and Strahan (2006). However, I also show that the findings are robust to alternative financial constraint measures constructed from small business data such as the Kauffman Firm Survey (KFS) or the 1998 Survey of Small Business Finances (SSBF).

For each mature firm i in sector j, the external financial dependence measure \( (EFD_{ij}) \) is defined as the difference between capital expenditures, \( CapEx \), and free cash flow, \( CF \), divided by capital expenditures:

\[ EFD_{ij} = \frac{\sum_t CapEx_{ijt} - \sum_t CF_{ijt}}{\sum_t CapEx_{ijt}} \]

A value of \( EFD \) smaller than 0 indicates that a firm has more cash flow than capital expenditures and thus tends to have funds available. A value larger than 0 indicates that a firm might be financially constrained as capital expenditures

A. More detailed discussion of the data set construction is in appendix B.
Bump et al. (2015).

to the SIC codes as the employment data only provide NAICS for the entire supply.

J

j

sector

sector

be an important reason for going public (Rajan & Zingales, 1998; Fazzari et al., 1988). The credit constraint measure for sector j is chosen to be the median value across all firms in sector j. The financial constraint measure is defined at the SIC-2 level, as is common in the literature. I then separate all sectors in the economy into composite sectors of high- and low-EFD, which are defined as those above and below the median external financial dependence measure, respectively.6

This paper uses a large number of control variables in some of the regressions that require additional data from a variety of sources. House price data are available at the quarterly frequency from the Federal Housing Finance Agency (FHFA) for many counties (Bogin, Doerner, & Larson, 2016). Population data, county-level employment, and income are obtained from the BEA. I use 2000 Census data to calculate the share of the county population that does not have a high school diploma, the share that has a four-year college diploma or higher, the share that has a high school diploma and possibly some college, and the share of county population that is black, white, and of “other” race. I rely on Small Area Income and Poverty Estimates (SAIPE) for data on the county-level poverty rate. The share of construction is computed from the County Business Patterns (CBP) from the Census Bureau. Industry characteristics data are taken from Compustat. I construct alternative measures of financial constraints from data of the Kauffman Firm Survey (KFS) and the Survey of Small Business Finance (SSBF).

B. Empirical Specification and Identification

The empirical specification uses employment growth in firm i in sector j in state s from 2007:Q4 to 2009:Q3 as the dependent variable. I estimate firm-level employment growth as follows:

\[
\delta_{ijs}^{2007-09} = \beta_0 + \psi_1 d_i + \psi_2 d_j + \beta_1 small_{ijs} + \beta_2 large_{ijs} + \beta_3 young_{ijs} + \beta_4 young \times small_{ijs} + \beta_5 high \times EFD_j \times young_{ijs} + \beta_6 high \times EFD_j \times large_{ijs} + \psi_3 X_{ijs} + \epsilon_{ijs}^{2007-09},
\]

where high – EFD_j is an indicator variable that takes the value 1 for sectors of high-EFD. X_{ijs} contains additional control variables used in the robustness checks detailed below, \delta_s are state fixed effects, and \beta_j are industry fixed effects. To include state fixed effects, I need to specify the location of a firm. For single-establishment firms, the location of the firm is simply the location of the single establishment. For the 5% of firms that are multieestablishment firms, I assign the location to the establishment that has the largest share of employment.7 A firm is classified as small (large) if it had fewer than 50 (more than 500) employees and is classified as young if it is less than five years old prior to the recession. I divide entrants into the size categories based on their employment size in the data at entry.8

The idea behind the EFD measure in Rajan and Zingales (1998) is that certain industries rely more on external finance than others because of certain industry characteristics. For instance, an industry that requires large capital expenditures (e.g., the manufacturing sectors that need machines for production) is likely more reliant on external finance than an industry that is human-capital intensive and requires only small capital expenditures (e.g., the IT industry, which may require only a laptop). The EFD measure is thus a proxy for the demand for credit in a given industry. This demand for credit, then, may or may not be constrained depending on the economic or financial conditions at the time.

Surveys, including some by the Kauffman Foundation and the Small Business Administration, document that small firms and start-ups rely on a variety of sources of financing that include personal funds, credit cards, home mortgages, home equity lines of credit, and small business loans. Under the assumption that many small and young firms need to borrow to set up their business and finance their operation, particularly during the start-up phase, the heterogeneity of firms due to industry or plant heterogeneity then implies that not all firms need to borrow to the same degree. In a model with production heterogeneity, for example, the most productive firms can rapidly accumulate enough profits to pay for the cost of start-up, while firms with lower productivity may take much longer to repay the entry cost. Both a software developer and a pharmacy may employ only a few people, but the pharmacy must finance a large inventory of medications, certain medical equipment, and its physical location, whereas the software developer may need only a few computers and can operate out of his or her own garage. It is then the combination of being small (young) and operating in an industry that requires external financing that identifies financially constrained firms. Larger firms in these industries tend to be less constrained and provide a control group. The difference between small (young) firms in low-EFD sectors

5 The observed credit usage is of course a function of both demand and supply.

6 To match financial data with employment data, I match the NAICS codes to the SIC codes as the employment data only provide NAICS for the entire sample length. I follow the matching of SIC-2 to NAICS-3 as in Duygan-Bump et al. (2015).

7 Similarly, for multieestablishment firms, I assign that industry in which the firm has its largest employment share.

8 As in Davis et al. (1996), and Haltiwanger et al. (2013), I use average employment between 2007 and 2009 for the classification to mitigate effects of regression to the mean.
and small (young) firms in high-EFD sectors then identifies a financing constraint effect combined with a high-EFD industry effect.

The remaining potential identification problem is that high-EFD industries may be more (or less) sensitive to changes in the business cycle. However, if the high-EFD effect is constant across firm size (age), then further differencing by the difference between large (old) firms in low-EFD and high-EFD industries removes the high-EFD industry effect. This is the difference-in-differences (DD) specification for the recession period 2007 to 2009.

However, a few potential concerns remain. One may be that there could be permanent differences in growth rates between small and large (young and old) firms across high- and low-EFD industries. In that case a further difference of the same comparison over a period without a financial shock identifies the tight credit effect. This is the difference-in-differences-in-differences (DDD) specification and compares the period 2004 to 2006 with the 2007 to 2009 period. Another potential concern is that it is important to separate the employment-reducing effect coming from financial constraints from the employment-reducing effect coming through the decline in aggregate demand. A larger reduction in employment in small (young) firms could be due to a reduction in demand that for some reason affected such firms in particular. For example, it could be that small and young firms tend to be in nontradable sectors such as restaurants, while larger firms could be concentrated in tradable sectors. This aggregate demand channel was particularly emphasized by Mian and Sufi (2014). The robustness section includes several modifications to the baseline, regressions to address these potential concerns. In the baseline, I include state × industry-fixed effects that account for any state industry–specific demand effects. I expand the baseline estimate to include a range of aggregate demand and industry-specific controls, or county × industry fixed effects.

### C. Results

In this section, I present the estimation results. First, I show the results for the effect of high-EFD on employment growth during the 2007–2009 financial crisis using a DD estimation. I then consider the composition of the sample of incumbents, entrants, and exiting firms and examine the role of each margin for the findings of the paper. I contrast the results for the whole sample with results of regressions controlling for entry and exit to highlight that the extensive margin (firm entry and exit) is of large importance for understanding employment growth during the financial crisis. I then report the results for the effect of high-EFD on employment growth using the DDD methodology.

In much of the empirical literature on firms, regressions are employment weighted (see Fort et al., 2013, and Haltiwanger et al., 2013). The regression results below, however, are equally weighted. Employment weighting implies that firms with a larger size receive a higher weight in the regression, while equal weighting implies that each firm receives the same weight in the regression. Economically, weighting by size can be interpreted as examining the effect of financial constraints on aggregate employment growth, while equal weighting shows how financial constraints are affecting the average firm. Thus, it is the question at hand that should determine which weighting is applied. Because this paper is focused on small and young firms (entrants have about six employees on average), the key question is how employment growth in the average firm is affected. The findings are likely to be weaker with an employment-weighted regression, however, as they would directly measure the aggregate implications of external financial dependence on employment growth.

A difference-in-differences estimator: Small versus large and young versus old. Generally small or young firms tend to be more dependent on bank financing than large or old firms as they do not have access to bond markets or other sources of external funds. As documented in data by the Kauffman Foundation, small and young firms also tend to rely on personal credit cards, personal loans, and home equity lines of credit (see Robb & Robinson, 2014). I thus begin by analyzing the differential effect of external financial conditions on small and large (young and old) firms. Subsequently, I narrow down which firms are driving the differential effect of EFD on small and large firms.

Column 1 in table 2 shows that when fixed effects are included to account for sector and state performance, employment growth in small firms in high-EFD sectors is, on average, 4.4 percentage points lower than for their low-EFD counterparts. Large firms in high-EFD sectors, however, grew about as fast as their low-EFD counterparts.

To difference out other effects that could have affected small firms differently from large firms, I now examine the double-difference of firm size and external financial dependence:

\[
(\hat{\beta}_{ml,high} - \hat{\beta}_{lrg,high}) - (\hat{\beta}_{ml,low} - \hat{\beta}_{lrg,low}) = -0.037^{***} (p-value = 0.006).
\]

The estimate of −0.037 means that the effect of the recession on small relative to large firms is about (negative) 3.7 percentage points larger in industries with high-EFD. Given that the average employment growth rate of firms in the economy is −10% (see the summary statistics in appendix B), the differential effect of high-EFD on small and large firms accounts for an economically significant part of this decline.

The existing literature highlights the importance of young firms for employment growth. Haltiwanger et al. (2013) find that in Census data from 1992 to 2005, once firm age is taken into account, firm size loses its significance in explaining employment growth. Column 2 examines the relevance of high-EFD for employment growth in young firms. In fact, the effect of high-EFD on employment growth in young firms

\[^9\hat{\beta}^{ij}\text{ are the differences relative to the omitted (medium) group.}\]
of observations is rounded to the nearest hundred.

- The number of observations is rounded to the nearest hundred.

Table 2.—Effect of High External Financial Dependence on Employment Growth, 2007–2009

<table>
<thead>
<tr>
<th>Dependent Variable: Employment Growth 2007:4–2009:3</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>0.096</td>
<td>-0.104***</td>
<td>-0.147***</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Young</td>
<td>0.450***</td>
<td>0.455***</td>
<td>0.367***</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Small × High-EFD</td>
<td>-0.044**</td>
<td>-0.020*</td>
<td>-0.018*</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Young × High-EFD</td>
<td>-0.073***</td>
<td>-0.072***</td>
<td>-0.049***</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Large</td>
<td>-0.007</td>
<td>0.029**</td>
<td>0.023***</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Large × High-EFD</td>
<td>-0.007</td>
<td>-0.012</td>
<td>-0.013</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Young × Small</td>
<td>0.092**</td>
<td>(0.046)</td>
<td>(0.046)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Young × Small</td>
<td>0.092**</td>
<td>(0.046)</td>
<td>(0.046)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>High-EFD</td>
<td>0.003</td>
<td>0.001</td>
<td>0.001</td>
<td>(0.001)</td>
</tr>
<tr>
<td>2-digit SIC × state FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>3,889,400</td>
<td>3,889,400</td>
<td>3,889,400</td>
<td>3,889,400</td>
</tr>
</tbody>
</table>

The dependent variable is the firm-level growth rate between 2007:Q4 and 2009:Q3. Standard errors are in parentheses. Significant at *10%, **5%, and ***1%. The number of observations is rounded to the nearest hundred.

Intensive versus extensive margin. Aggregate data indicate that the entry and exit margins were of particular importance for employment growth during the financial crisis. The definition of the employment growth rate allows me to further study the importance of the extensive margins because the growth rate is well defined for firm entry and firm exit. In this section, I first show again the DD estimator for young versus old and small versus large firms (see table 3, column 1). Next, I illustrate the importance of the entry and exit margin by limiting the sample to firms that are in the data in both 2007:Q3 and 2009:Q4 (i.e., a sample of “continuing firms”; firms that entered or exited during this period were removed). I limited the sample further by examining a sample that includes the entering firms but not the exiting firms (“Entry”). Finally, I consider a sample that includes the exiting firms but not the newly entering firms (“Exit”). These subsamples help illustrate the importance of the entry and exit margins.

The DD estimator for young versus old firms is −0.057, somewhat larger in absolute value than the findings on small versus large firms. When I restrict the sample to only the continuing firms (column 2), the DD estimator indicates that young firms grew 1.8 percentage points less through high EFD than old firms. This finding illustrates that the extensive margin is key for the findings on financial constraints. By separately considering samples without the exiting firms (column 3), we see that including entering firms reduces the DD estimator to −0.034. If one includes only the exiting firms, the DD estimator is −0.029. Consequently we can conclude that the extensive margin is key for the effect of financial constraints on employment growth. In particular, firm entry is somewhat more important than firm exit in generating the main finding. The DD estimator for small versus large firms shows a somewhat smaller importance for the extensive margin overall because the DD estimator in the sample of continuing firms is closer to the whole sample estimator than the DD for young versus old firms is.

The analysis includes industry × state fixed effects, thus estimating firm-level employment growth in small versus large firms within the same state and industry. The underlying identifying assumption is that changes in demand are not differential by firm size or age within an industry in

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10 Including an additional control for large and young and the interaction of large and young and high-EFD does not significantly alter the key findings.
any given state. However, the findings may be confounded if differences in growth rates in small and large (young and old) firms across high- and low-EFD sectors are permanent and are not a result of a financial constraints during the 2007–2009 recession. The next section considers a methodology that addresses this concern.

A difference-in-differences-in-differences estimator. The purpose of this section is to alleviate concerns that the difference between high- and low-EFD sectors for small and large firms might be present at all times, not just during the recent financial crisis. In the presence of such permanent differences between high- and low-EFD sectors, a further difference of the same comparison over a time period without a financial shock identifies the tight credit effect. In this section, I extend the analysis to include not only the difference between small and large firms in high-EFD and low-EFD sectors but also the difference in time between the 2004–2006 and 2007–2009 periods. That is, for each regression, I computed for each firm one growth rate for the 2007–2009 period and one growth rate for an equally long period from 2004 to 2006. The idea is that in normal times, there might be a difference in growth rates in low- and high-EFD sectors driven by their structural differences entirely unrelated to external finance. It is thus important to express the findings for the 2007–2009 recession relative to this baseline. I select the 2004–2006 period as the baseline, but the findings are robust to using other periods of equal length after 2001. Table 4 shows the result of a single regression of firm-level employment growth on size and the interactions with high-EFD and a financial crisis dummy. The main finding in this table is that the interactions between size and the financial crisis dummy are negative. Moreover, the interaction between small and high-EFD is negative during the financial crisis, while the interaction between large and high-EFD is positive. The interaction between size and high-EFD have reversed signs in the absence of the financial crisis interaction.

I report the triple-difference estimation results for small and large firms:11

\[
\begin{align*}
(\hat{\beta}_{sml, high} & - \hat{\beta}_{lrg, high}) - (\hat{\beta}_{sml, low} - \hat{\beta}_{lrg, low})_{2007-09} \\
- (\hat{\beta}_{sml, high} & - \hat{\beta}_{lrg, high}) - (\hat{\beta}_{sml, low} - \hat{\beta}_{lrg, low})_{2004-06} \\
= -0.077^{***} (p-value < 0.001). 
\end{align*}
\]  

They show that high-EFD reduced employment growth by 7.7 percentage points in small firms relative to large firms in the 2007–2009 period relative to the 2004–2006 period. That is, the effect of high-EFD is even stronger during the financial crisis than it appeared from the difference-in-differences estimator. Clearly, the selection of the baseline matters, and the use of the 2004–2006 period might be imperfect, as it is a period of extremely loose credit. However, choosing another period as the baseline between 2000 and 2006 in my estimations always yielded triple-difference estimators larger than the 3.7 percentage point decline of the difference-in-differences estimator. The relative decline of 7.7 percentage points can thus be interpreted as an upper bound of the effect of financial constraints, while the relative decline of 3.7 percentage points can be interpreted as a lower bound. Similar to the DDD estimator for small and large firms, I can compute the DDD estimator for young versus old firms. Here is the triple difference estimation results for young and old firms:12

\[
\begin{align*}
(\hat{\beta}_{yng, high} & - \hat{\beta}_{old, high}) - (\hat{\beta}_{yng, low} - \hat{\beta}_{old, low})_{2007-09} \\
- (\hat{\beta}_{yng, high} & - \hat{\beta}_{old, high}) - (\hat{\beta}_{yng, low} - \hat{\beta}_{old, low})_{2004-06} \\
= -0.088^{***} (p-value < 0.001). 
\end{align*}
\]

The coefficient of −0.088 is both statistically significant and economically large. The DDD estimations for young versus

---

11 Based on estimations in column 1 of table 4.

12 Based on estimations in column 2 of table 4.
old are somewhat larger than the corresponding DD estimator of $-0.073$.\footnote{For completeness, I provide set of robustness checks for the DDD estimators in the appendix.}

The previous section showed that the findings of the DD estimator are not driven by permanent differences between high- and low-EFD industries and in fact likely underestimate the strength of the effect as the DDD estimates are larger for both the small versus large and also the young versus old estimate. Nonetheless several concerns regarding the validity of results remain. For example, the findings may be confounded by some demand effects or industry characteristics that vary among age and size groups.

D. Robustness

This section provides several variations and extensions of the baseline to robustness checks for the difference-in-differences estimators.$^{14}$ First, I compare the DD estimator to one for the dot-com bust of 2001. The dot-com bust was not a financially driven recession, and one would thus expect that the DD estimator would be different from the findings for the 2007–2009 recession if the latter estimator indeed captures the effect of financial constraints. Second, I include a number of regional controls to capture any potential effect of local demand conditions (such as house prices), as well as sector-specific controls in the regressions. Third, the baseline regression results are based on a financial constraint measure from Compustat data. Because at most a few percent of firms in the sample are publicly listed, I report robustness checks based on financial constraint measures from small-business data.$^{15}$

**Dot-com bust versus financial crisis.** This section compares the difference-in-differences estimator for the financial crisis with the corresponding estimator for the period of the 2001 dot-com bust.\footnote{One could argue that robustness checks should be conducted using the DDD estimator. To alleviate concerns about the selection of the DD estimator for the robustness checks, I include a set of identical robustness check for the DDD estimator in appendix D.} The main finding, as shown in table 5, is that the DD estimator for the 2001–2002 period differs from the one for the Great Recession. However, the DD estimator of small relative to large firms for 2001–2002 is

$$2001 : (\hat{\beta}^{\text{small, high}} - \hat{\beta}^{\text{large, high}}) - (\hat{\beta}^{\text{small, low}} - \hat{\beta}^{\text{large, low}}) = 0.0328^{***} \text{ (p-value < 0.001).}$$

(6)

The DD estimator for young versus old firms for the 2001 recession is

$$2001 : (\hat{\beta}^{\text{young, high}} - \hat{\beta}^{\text{old, high}}) - (\hat{\beta}^{\text{young, low}} - \hat{\beta}^{\text{old, low}}) = 0.0184^{***} \text{ (p-value < 0.001).}$$

(7)

This finding confirms that the financial constraints had a pronounced effect on employment growth during the Great Recession; however, I do not find the same effect during the 2001 recession. Because the 2001 recession was not one driven by financial shocks, it shows that on average, in normal times small firms in high-EFD sectors grow faster than their large counterparts. The DDD estimator similarly suggested this to be the case.

Controlling for aggregate demand, county, life cycle, and industry characteristics. Previously, I argued that the DD methodology should eliminate the effect of other shocks affecting the economy during the Great Recession. However, the methodology may not be sufficient under certain scenarios. Mian and Sufi (2014) argue that aggregate demand was primarily driven by a slump in house prices and that counties with a large decline in house prices experienced a larger decline in nontradable employment. Mian, Rao, and Sufi (2013) show that counties with high debt-to-income ratios in 2006 experienced a larger decline in household expenditures during the financial crisis. The DD methodology would fail to account for the aggregate demand effect correctly if it were true that small firms in high-EFD sectors were more likely than large firms to be located in areas with large aggregate demand effects. Furthermore, Mian, Rao and Sufi (2011) document that a significant fraction of the rise in U.S. household leverage between 2002 and 2006, as well as the increase in defaults between 2006 and 2008, can be explained by borrowing against rising house prices leading up to the recession. To the regressions presented earlier, I therefore add the growth rate of the house price index (HPI) at the county level between 2002 and 2006 as additional control. Using contemporaneous house price growth would raise the concern that employment declines during the crisis might actually be driving a decline in home prices. The reason for adding

| Table 5.—Effect of High External Financial Dependence in the 2001 Recession |
|---------------------------|---------------------------|---------------------------|---------------------------|
|                          | (1)                      | (2)                      | (3)                      | (4)                      |
| Small                    | $-0.110^{***}$           | $-0.137^{***}$           | $-0.204^{***}$           |
|                          | (0.007)                  | (0.005)                  | (0.008)                  |
| Young                    | $0.117^{***}$            | $0.123^{***}$            | $0.053^{***}$            |
|                          | (0.011)                  | (0.011)                  | (0.007)                  |
| Small × High-EFD         | $-0.017^{***}$           | $-0.018^{***}$           | $-0.013^{***}$           |
|                          | (0.004)                  | (0.003)                  | (0.004)                  |
| Young × High-EFD         | $0.018^{***}$            | $0.018^{***}$            | $0.053^{***}$            |
|                          | (0.006)                  | (0.006)                  | (0.012)                  |
| Large                    | $0.047^{***}$            | $0.053^{***}$            | $0.051^{***}$            |
|                          | (0.006)                  | (0.006)                  | (0.006)                  |
| Large × High-EFD         | $-0.050^{***}$           | $-0.055^{***}$           | $-0.053^{***}$           |
|                          | (0.008)                  | (0.008)                  | (0.008)                  |
| Young Small              | $0.073^{***}$            | $0.073^{***}$            | $0.073^{***}$            |
|                          | (0.013)                  | (0.013)                  | (0.013)                  |
| Young Small × High-EFD   | $-0.026^{**}$            | $-0.026^{**}$            | $-0.026^{**}$            |
|                          | (0.011)                  | (0.011)                  | (0.011)                  |
| 2-digit SIC × state FE   | Yes                      | Yes                      | Yes                      | Yes                      |
| Observations             | 3,397,200                | 3,397,200                | 3,397,200                | 3,397,200                |

The dependent variable is the firm-level growth rate between 2001:Q1 and 2002:Q1. Standard errors are in parentheses. Standard errors are clustered by state. Significant at *10%, **5%, and ***1%. The number of observations is rounded to the nearest hundred.
precrisis house price growth is to avoid this potential endogeneity issue. Based on the findings by the authors discussed above, we should thus expect that the aggregate demand channel led to employment losses that were particularly strong in areas with large house price increases before the crisis.

In addition to house prices, a large number of other county characteristics could potentially affect the findings, such as the share of construction in employment, the unemployment rate, the fraction of nonwhite population, the poverty rate, the ratio of population with a college degree, the sector capital intensity, and five-year life cycle growth by six-digit NAICS sector. County industry fixed effects absorb the effect of any shocks that were particular to a specific county or a three-digit NAICS industry in a county.

Table 6 presents the results. Columns 1 to 3 present the results using county-industry fixed effects. Columns 4 to 6 present results controlling for a large range of industry characteristics, as well as their interaction with firm age and firm size. The findings thus provide support for the hypothesis that financial constraints were an important factor for employment growth beyond the effects of the aggregate demand channel. The appendix contains more robustness checks and reports results for some key county-level controls, which were not reported in the tables above.

Table 7 presents the DD estimators based on table 6. Overall the coefficients are similar to the baseline.

Finally, as an alternative way to address the concerns I have noted, I present a set of results that include county-industry (three-digit NAICS) fixed effects. Including county fixed effects alone would imply that the regression exploited only within-county variation, avoiding any potential concerns coming from unobservables county differences in local factors. County industry fixed effects absorb the effect of any shocks that were particular to a specific county or a three-digit NAICS industry in a county.
firms. I construct two measures of financial constraints from small business data and add a market-based measure of credit constraints as a robustness check.

To do so, I first construct a measure of financial constraints from the 1998 Survey of Small Business Finance (SSBF) following Cetorelli and Strahan (2006) and Duygan-Bump et al. (2015). The SSBF collects information on smaller firms with fewer than 500 employees. I construct bank dependence for each firm in the SSBF by calculating the share of assets financed with debt from financial institutions. Following the construction of the Compustat financial constraints measure, the sectoral measure is then constructed using the median values for each two-digit SIC category.

Second, I construct a measure of financial constraints from the Kauffman Survey (KFS), a stratified random sample of about 5,000 firms started in 2004 that are surveyed annually. I construct the debt-to-total-asset ratio for pre-2007 years for all available two-digit NAICS sectors. The sector-level measure is then constructed using the median values for each two-digit NAICS category.

The baseline external financial dependence measures and the two measures constructed above are based on balance sheet data. As a third alternative measure of financial constraints I rely on a market-based measure related to the work of Gilchrist and Zakrjašek (2012). Gilchrist and Zakrjašek (2012) construct an economy-wide credit spread measure that has predictive power for future economic activity. In this paper, I rely on a sector level (three-digit NAICS) credit spread data. In particular, I use the increase in sector-level credit spread between 2007 and 2009 as a measure of the size of the credit shock. This is a more direct measure of the credit supply shock compared to the other measures used so far. This measure also helps to address a concern regarding the heterogeneity of the credit supply shock. The identification strategy employed in this paper recovers credit demand elasticities correctly only if supply shocks are uniform across sectors, regions, and firm sizes and ages. The previous section controlled for regional and age- and size-specific effects of the crisis; this section addresses the concern that the credit supply shock may in fact have varied across sectors.

For the SBFF and KFS measures, high-EFD and low-EFD sectors are based on the median across sectors. For the market-based measure of sectoral bond spreads, high-EFD stands for the increase in sector corporate bond spreads between 2007 and 2009 (at the three-digit NAICS level) and is thus a continuous measure. Table 8 shows the key results using financial constraint measures from small business data. Columns 1 to 3 show the results using the Survey of Small Business Finance, columns 4 to 6 show the results using the Kauffman Survey, and columns 7 to 9 show the findings using sectoral corporate bond spread measure. The findings across all three measures broadly confirm those using the Compustat EFD measure. The DD estimator for small versus large across the two small business data financial measures is about 6% and about 3.5% for the corporate bond spread measure (see table 9), whereas it was about 4% using the Compustat EFD measure in the baseline.

The DD estimator for young versus old across the three measures has a larger range than the DD estimator for small versus large. The young versus old DD is about 6% for the SSBF and the corporate bond spread measure and about 11% for the KFS measure (see table 9). The Compustat-based DD estimator for young versus old firms in the baseline fits squarely into this range, with a value of about 7%.

E. Aggregate Implications of Financial Constraints of Small and Young Firms

I follow the approach of Chodorow-Reich (2014) in calculating the aggregate implications of the estimates in section IIIC. In order to estimate the aggregate implications in this counterfactual exercise, one has to make the following assumptions.

Assumption 1 (partial equilibrium). The overall effect on employment is the sum of the direct employment effects on each firm.

Assumption 1 rules out any general equilibrium effects through price or wage adjustments. Taking such effects into account would require a general equilibrium model.

Assumption 2 (low-EFD firms are unconstrained). Firms in low-EFD sectors are unconstrained, and financial constraints affect firms only through high-EFD.

In order to compute aggregate implications of a credit supply shock, one needs to assume the existence of an unconstrained category of firms, as in Chodorow-Reich (2014) or have a good measure of the credit supply shock for the least constrained category. In the context of this paper, the

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**Table 7.** Effect High External Financial Dependence on Employment Growth, 2007–2009: Aggregate Demand and Industry Controls

<table>
<thead>
<tr>
<th></th>
<th>County-Industry FE Controls</th>
<th>Demand Controls</th>
<th>Industry FE Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>DD small versus large</td>
<td>−0.030***</td>
<td>−0.037***</td>
<td>−0.044***</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.007)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>DD young versus old</td>
<td>−0.069***</td>
<td>−0.070***</td>
<td>−0.051***</td>
</tr>
<tr>
<td></td>
<td>(&lt; 0.001)</td>
<td>(&lt; 0.001)</td>
<td>(&lt; 0.001)</td>
</tr>
</tbody>
</table>

2-digit SIC × State FE Controls

- No
- Yes
- No
- Yes
- Yes
- No
- Yes
- Yes

Observations 3,889,400 3,775,400 3,761,000

This table shows difference-in-differences estimators for small versus large and young versus old for three alternative specification to control for aggregate demand and industry effects. Column (1) shows the DD estimator based on including county-industry fixed effects in the estimation, column (2) shows the DD estimator based on a specification that includes controls for demand, the results shown in column (3) are based on a specification that includes controls for industry characteristics. p-values are in parentheses. Significant at ***1%. The number of observations is rounded to the nearest hundred.
unconstrained category has to be low-EFD firms. Assumption 2 is quite conservative. If low-EFD firms were also unconstrained, the estimates will underestimate the true effect of the credit supply shock, as I will discuss. Assumptions 1 and 2 are similar to the assumptions in Chodorow-Reich (2014), but due to the presence of entry and exit in the BLS data, the calculation of aggregate implications in this paper requires an additional assumption.

**Assumption 3** (no credit supply effect on start-ups). The credit supply shock did not affect start-ups or potential start-ups.

Assumption 3 is required for two reasons: (a) potential start-ups are not observed and any effect of financial constraint on changes in start-up decisions cannot be taken into account to compute aggregate implication, and (b) while start-ups are observed, they get assigned a growth rate of +2, the upper bound of the DHS growth rate. Entrants are, by construction, at the upper bound of the DHS growth rate and thus cannot be assigned a higher growth rate in a counterfactual. Taking effects on start-ups into account would require an empirical model of start-up decisions, which would require additional information on these start-ups, such as balance sheets. While this is clearly desirable, it is beyond the scope of this paper. Furthermore, it is not possible to make inferences about the impact on potential start-ups as these are unobserved. Assumptions 2 and 3 mean that the partial equilibrium aggregate effects of a credit supply shock are likely underestimated. First, it is unlikely that low-EFD firms were entirely unconstrained. To the extent that the credit supply shock reduced employment growth in low-EFD firms, the aggregate implications in this paper will underestimate the aggregate effect. Second, the credit supply shock possibly affected entrants as well as potential entrants, which in turn would increase the aggregate effect of a credit supply shock.

Given the assumptions above, it can be informative to compute the aggregate implications of the estimates in section IIIC. This paper argued that the DD estimator can identify the effect of a credit supply shock on small relative to large firms. Consequently, the aggregate implications of financial constraints can then be calculated by comparing the employment evolution in the (fitted) data with the employment evolution in a counterfactual in which financial constraints affected small firms in the same way as large firms—a DD estimator of 0 (and similar for young and old).

---

21 In Chodorow-Reich (2014), the unconstrained category is the most liberal lending syndicate.

22 As new entrants are assigned a growth rate of +2 (by construction of the growth rate measure defined by Davis et al., 1996), the counterfactual cannot further increase their growth rate. It should also be taken into account that these calculations do not change the number of firms in the sample. For example, the number of start-ups may have been higher in the absence of a credit supply shock for young firms.
Define the counterfactual growth rate of a firm $i$ of group $k$, $k \in \{\text{small high-EFD, young high-EFD}\}$, as

$$g_{i,2007-09}^{k,\text{cf}}(\text{DD} = 0) = E \left[ g_{i,2007-09}^{k,\text{cf}} | \text{DD} = 0 \right] = \hat{g}_{i,2007-09}^k + \hat{\beta}_{\text{DD}},$$

(8)

where $\hat{g}_{i}^k$ denotes the fitted value from the regression of firm type $k$ and $\hat{\beta}_{\text{DD}}$ is the corresponding point estimate of the difference-in-differences estimator. For low-EFD small/young firms and all large firms, the counterfactual growth rate equals the fitted growth rate. Duygan-Bump et al. (2015) also uses only the differential effect of financial constraints on small relative to large firms for computing aggregate implication.

Following Chodorow-Reich (2014), let $T$ denote the mapping from symmetric employment growth rates to the end of the period employment level, taking the initial level as given:

$$T(x) = \frac{1 + 0.5x}{1 - 0.5x} n_{i,2007}.$$  

(9)

Using equation (9), one can compute the implied employment level from the counterfactual growth rate as $\hat{n}_{i,2009} = T \left( \hat{g}_{i,2007-09}^k \right)$. Furthermore, let the fitted value employment be $\hat{n}_{i,2009} = T \left[ \hat{g}_{i,2007-09} \right]$. We can then calculate the aggregate effect as

$$\sum_{i \in k} \left( \hat{n}_{i,2009} - \hat{n}_{i,2009} \right) \sum_{i} (n_{i,2007} - n_{i,2009}).$$

(10)

Table 10 reports the results.

The aggregate effect of the differential impact of financial constraints on small relative to large and young relative to old firms is quantitatively important. The differential effect on small firms accounts for about 9% to 10% of the decline in employment observed during the recession. Meanwhile, the effect on young firms accounts for about 15% of the overall employment decline. It is important to note that these estimates cannot be simply added up to account for the total effect of financial constraints on small and young firms as firms can be included in both categories. The differential effect of credit constraints accounts for about one-third of the overall decline in employment in young firms as well as small firms. Whereas employment in young firms overall fell more than in small firms (see table 1), the importance of financial constraints for the employment decline in small and young firms is similar as the overall decline in young firms in my sample is larger than in small firms.

Using a related identification strategy, Duygan-Bump et al. (2015) find that financial constraints of small firms can account for about 8% of the increase in unemployment; however, this does not map one-for-one into employment growth. Chodorow-Reich (2014) finds that the effect of the loan supply shift for small and medium firms (fewer than 1,000 employees) states that the credit supply shift accounts for 30% to 50% of the decline in employment in small and medium firms, which leads him to conclude that the credit supply shock may account for 20% to 33% of the overall decline in employment in the population. At the lower range of estimates, using small business lending data, Greenstone, Mas, and Nguyen (2014) find that the credit supply shock can account for up to 5% of the aggregate employment decline. At the upper range of estimates, Mondragon (2015) finds that the credit supply shock can account for more than 50% of the aggregate employment decline.

The methodology used in this paper allows for the calculation of the aggregate implications using the differential effect of financial constraints on small (young) relative to large (old) firms. To the extent that a credit supply shock also affected low-EFD firms or (potential) entrants, the above calculations are going to underestimate the aggregate effect. Moreover, a shock affecting young firms and potential entrants may in fact have a persistent effect on future economic activity if it prevents, for example, the start-up of superstar firms (e.g., the next Apple or Amazon) or inhibits the growth of such firms. Gourio et al. (2016) show that a 1-standard deviation reduction in the number of start-ups lasts ten years or longer and implies a decline of real GDP of 1% to 1.5% at its trough.

### IV. Conclusion

This paper provides evidence for the implications of financial constraints for young and small firms during the Great Recession. I empirically examine whether firm financial constraints negatively affected employment growth, using financial data from Compustat and confidential employment data from the BLS, and compare the effect on firms by age and size.

I find that financial constraints reduced employment growth in small and young firms significantly during the 2007–2009 recession and that the findings for small firms
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are driven by young firms. The results further indicate that the entry and exit margins are important to understanding the effects of financial constraints.

The findings suggest that it is important for policymakers to seriously consider the business conditions for small firms, and particularly young firms, in policy design. The effect of financial conditions on start-up decisions remains a wide open question. More research is needed to gain a better understanding of the implications of financial conditions for potential entrepreneurs.

REFERENCES


