

# Firm Entry and Employment Dynamics in the Great Recession\*

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August 2014

## Abstract

The 2007-2009 recession is characterized by: a large drop in employment, an unprecedented decline in firm entry, and a slow recovery. Using confidential firm-level data, I show that financial constraints reduced employment growth in small relative to large firms by 4.8 to 10.5 percentage points. The effect of financial constraints is robust to controlling for aggregate demand and is particularly strong in small young firms. I show in a heterogeneous firms model with endogenous firm entry and financial constraints that a large financial shock results in a long-lasting recession caused by a “missing generation” of entrants.

**Keywords:** employment, firm entry, financial crisis, small business, financial friction, slow recovery, start-ups

**JEL:** E24, E32, E44, G01, L25, J2

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\*The views expressed in this paper are those of the author and do not necessarily reflect the views of the Federal Reserve Board or the Federal Reserve System. This research was conducted with restricted access to Bureau of Labor Statistics (BLS) data. The views expressed here do not necessarily reflect the views of the BLS or the U.S. government. First draft: March 2012. I am deeply indebted to François Gourio, Simon Gilchrist, Robert G. King, and Adrien Verdelhan. I thank Nicola Cetorelli and Philip E. Strahan for providing their data and code. In addition, I thank Marco Bassetto, Jeffrey Campbell, Sanjay Chugh, Gabriel Chodorow-Reich, Christian Hellwig, Aubhik Khan, John M. Roberts, Walter Steingress, Mark Wright, Egon Zakrajsek, and seminar participants at U Ottawa, U Bonn, Boston U, U Mannheim, U Cambridge, UNC-KF, CREi, ECB, SFU, JHU, KC Fed, Fed Board, Richmond Fed, Boston Fed, Chicago Fed, ES NASM 2012, BU/BC GLMM, MWMM Fall 2013, MAFFAP 2013, Macroeconomics and Survey Data Conference 2013, and the NBER Summer Institute 2014 (capital markets and the economy) for their helpful comments and suggestions. I thank Jessica Helfand, Michael LoBue, and Emily Thomas for support with the BLS QCEW Database. All remaining errors are mine.

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# 1 Introduction

The 2007-2009 recession and the subsequent economic recovery in the United States differed from most historical recessionary periods. The Great Recession exhibited an unprecedented 5 percent decline in the number of firms, which was driven by a 25 percent decline in the number of entrants between 2007 and 2010. Moreover, it is one of only two recessions since the late 1970s during which aggregate lending declined.<sup>1</sup> Finally, the financial crisis was followed by a slow recovery in macroeconomic aggregates, while deep recessions after World War II typically feature rapid recoveries with strong increases in output and employment.

In this paper, I investigate both theoretically and empirically, the relationship between the financial constraints of small and large firms, firm entry, and a slow economic recovery following the financial crisis. This paper contributes to the literature twofold.

First, I use a confidential dataset on firm-level employment from the Bureau of Labor Statistics (BLS). Unlike the existing empirical literature, which typically ignores the 95 percent of firms that have fewer than 50 employees, this study examines employment growth of the “universe” of firms during the 2007-2009 recession in the United States. The results imply that external financial constraints account for a reduction of employment growth in small firms relative to large firms during 2007-2009 by 4.8 to 10.5 percentage points. I show that this result is driven primarily by young firms. Furthermore, this study documents the importance of entry and exit margins to account for the differential effect of external financial dependence on small and large firms.

Second, I propose a novel explanation for slow recoveries in the aftermath of a financial crisis: a “missing generation” of entrants. I argue that such recoveries are the result of a credit crunch: a reduction in bank lending most directly affects small and young, bank-dependent firms. The lack of external funds prevents the formation of new businesses, which creates a “missing generation” and leads to a persistent reduction in labor demand. A slow recovery then follows as the reduction in the number of firms in the economy is only gradually reversed.

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). An external financial dependence measure on the sectoral level is constructed 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 needs in a given sector by comparing firm cash flows with capital expenditures over multiple years,

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<sup>1</sup>The other being the 1991 recession, which was a result of the savings and loan crisis (Contessi and Francis (2011)).

which allows me to construct sectors of high and low external financial dependence. I find that high external financial dependence (high EFD) reduced employment growth in small firms by 4.8 to 10.5 percentage points relative to large firms during the 2007-2009 recession. This confirms the notion that small firms are more affected by credit constraints. I further show that, in particular, young firms in high EFD sectors reduced employment growth relative to firms in sectors of low external finance dependence (low EFD). The conditional expected growth rate for young, small firms in high EFD sectors was reduced by more than 30 percent relative to their counterparts in low EFD sectors. Firm entry and exit are important factors that can explain this observation. The conditional expected growth rate of small young firms is reduced by only about 20 percent through high EFD in the sample without entering and exiting firms. Finally, I find that the aggregate demand channel, as pointed out by Mian and Sufi (2012), does not account for the main finding of this paper on the effects of external financial dependence on small versus large and young versus old firms. I therefore provide evidence that the credit channel is another important mechanism for better understanding the Great Recession.

I then develop a quantitative model that generates a persistent recession through a substantial decline in firm entry. The model relies on the following key assumptions: Firms are heterogeneous in productivity and are subject to labor adjustment costs. They have access to default-able debt, which generates endogenous borrowing constraints. Entry is endogenous; potential entrants that decide to enter incur set-up costs and have to finance a fraction of these costs externally. The model is calibrated to match the firm size distribution in order to investigate the effect of financial shocks on small and large firms.

A temporary financial shock – a three year reduction in the parameter that determines the recovery rate in default – increases the cost of external finance and leads to a large reduction of firm entry because potential entrants cannot obtain sufficient funds. This produces a “missing generation” of entrants. The “missing generation” implies that there are too few young firms to replace the exiting large firms. A prolonged recession follows, with employment only gradually returning to its pre-recession level.

The empirical results and the quantitative model show that financial constraints most directly affected small young firms’ employment through entry and exit during the 2007-2009 period. The financial crisis then propagated itself through the financial constraints of small young firms, leading to a reduction in the number of firms and a slow recovery.

This paper is at the intersection of several strands of literature. First, it is related to the literature on heterogeneous firms and financial constraints. It is closely related to Bassetto, Cagetti and De Nardi (forthcoming), who study a model the effect of financial shocks in a model with an entrepreneurial and a corporate sector. The main finding is that the

entrepreneurial sector is more strongly affected by a financial shock and that the financial shock has a persistent effect on the economy. Other recent contributions to this literature include Gilchrist, Sim and Zakrajsek (2010), Arellano, Bai and Kehoe (2012), and Khan and Thomas (2013). These contributions succeed at generating the initial large decline in output during the Great Recession. However, the models have a fixed number of firms in the economy and suggest a fast recovery following a financial crisis.

Second, the paper is related to the literature on firm entry and exit and, in particular, to Samaniego (2008), Lee and Mukoyama (2012), and Clementi and Palazzo (2013). The entry setup of my paper is most closely related to the one in Clementi and Palazzo (2013). In the setup of the aforementioned papers, however, debt has no role in the entry decision of firms. In my model, external finance is a key factor for entry dynamics. In a recent contribution, Clementi, Khan, Palazzo and Thomas (2014) extend the analysis of Clementi and Palazzo (2013) to the general equilibrium. The authors concur with my finding that a large decline in entry can lead to a slow recovery through a “missing generation” of firms.

Third, my quantitative model shares the focus on slow recoveries with Reinhart and Rogoff (2009a), Reinhart and Rogoff (2009b), Bachmann (2012), Berger (2012), and Gali, Smets and Wouters (2012). Reinhart and Rogoff provide empirical evidence that financial crisis tend to be followed by slow recoveries. Bachmann’s model generates jobless recoveries in response to shallow recessions, but predicts a rapid recovery in response to a deep recession. Berger (2012) develops a heterogeneous firm model of selective firing. The addition of selective firing can generate a substantial jobless recovery, even in response to a severe recession. However, both papers lack any role for credit.

Fourth, an empirical literature related to this paper examines the determinants of the employment decline during 2007 and 2009. Chodorow-Reich (2014) provides evidence, using syndicated loan data, that lender health matters for employment outcomes in small- and medium-sized publicly traded firms. Mian and Sufi (2012) provide evidence that a drop in aggregate demand is the main driver of employment losses during the Great Recession. The most closely related paper in terms of empirical methodology is Duygan-Bump, Levkov and Montoriol-Garriga (2010). These authors use Compustat data to derive financial constraint measures, as in the present paper. They find that workers in small firms in sectors of high EFD are more likely to become unemployed. However, lacking firm data the authors can not study the importance of firm age and the entry and exit margins. Finally, Benmelech, Bergman and Seru (2011) examine the impact 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.<sup>2</sup>

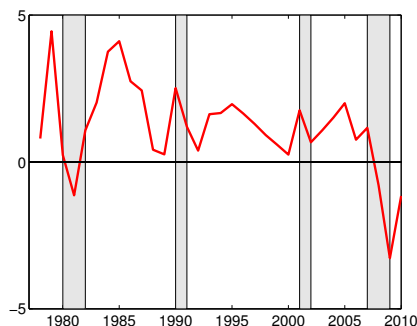
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<sup>2</sup>Earlier studies that link financial constraints to firm size and firm age include Gertler and Gilchrist

## 2 Firm Entry 2007-2009

In this section I review stylized facts on firm entry and the firm size/age distribution during the financial crisis of 2007-2009.<sup>3</sup>

Figure 1: **Percent Change in Number of Firms in the U.S. Economy, 1978-2010**



*Notes:* The figure shows the percentage change in the number of firms in the economy. Gray shaded areas indicate NBER recession episodes. *Source:* Business Dynamics Statistics (BDS).

I use annual Business Dynamics Statistics (BDS) data that are available from 1978 to 2011. Figure 1 shows the net change in the number of firms from 1978 to 2010. The figure illustrates that the net change in the number of firms is highly volatile. The 2007-2009 recession is distinct from prior recessions in that it is the only recession during which the number of firms declined over multiple years; the aggregate decline from 2007 to 2010 was more than 5 percent.<sup>4</sup>

Figure 2, panel (a), shows the number of entering firms per year since 1978. The number of entrants varies significantly over time. Its largest decline clearly occurred in the 2007-2009 recession, when it dropped more than 25 percent. Figure 2, panel (b), displays the last decade of data on entrants and the number of firms by firm age.<sup>5</sup> Naturally, there are fewer firms in the older age groups than in the younger groups, as over time some firms exit. Moreover, the figure shows a 25 percent decline in startups (firms less than one year old) between 2006 and 2010. Subsequently, this decline moves through the age distribution

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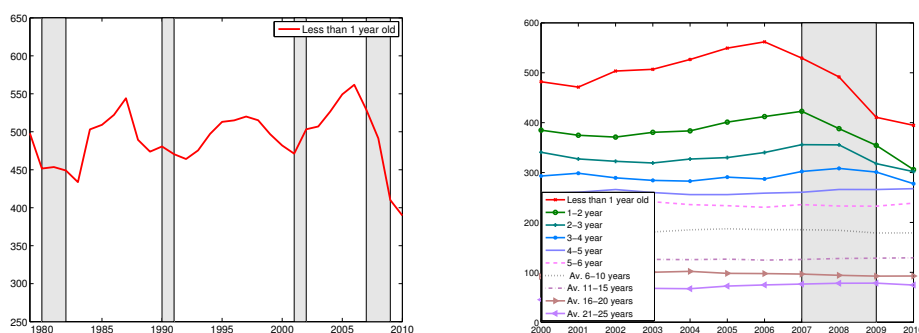
(1994), Cooley and Quadrini (2001).

<sup>3</sup>Some related facts have been documented in existing work: see Hellerstein and Koren (2006), Duygan-Bump et al. (2010), Gilchrist et al. (2010), and Moscarini and Postel-Vinay (2012), among others. The Appendix provides additional facts on small business lending, home mortgages, and spreads of financial variables.

<sup>4</sup>The BDS data report exit and entry rates not by firms but by establishment only. During the 2007-2009 recession, the establishment entry rate fell by about 25 percent, while the exit rate increased by about 15 percent.

<sup>5</sup>Data for all displayed age groups are available only since 1998.

Figure 2: **Entry and the Number of Firms by Firm Age**



(a) Number of Entrants per year

(b) Number of Firms by Firm Age

Notes: The vertical axis is denoted in thousands of firms. Source: Business Dynamics Statistics (BDS).

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.

Another way to look at the data is to consider firm size. Table 1 provides details on the decline in the number of firms in 2007-2009 by firm size class. The first column shows that in 2007 more than 5 million firms had less than 50 employees. Small firms (those firms with fewer than 50 employees) are important for the macroeconomy because 95 percent of firms are small and they account for 30 percent of aggregate employment. Large firms ( 500 or more employees) account for less than 0.5 percent of firms but account for 48 percent of aggregate employment.

The second column in Table 1 shows that the number of small- and medium-sized firms fell significantly more than the number of large firms between 2007-2009. This is true despite the fact that this table does not take into account the composition bias (i.e., medium-sized firms that reduced employment in 2007 might be classified as small firms in 2009). This would lead the data to understate the true effect on the number of small firms.

The aggregate data presented above suggests that the financial crisis stands out from historical recessions by virtue of its impact on young (startup) and small firms. The 2007-2009 recession originated in the financial sector of the United States. It is thus important to examine to what extent financial constraints can explain the evolution of employment and the particularly strong impact on young and small firms during this period. I study the importance of financial constraints for firm employment growth in the next section.

Table 1: **Number of Firms: 2007-2009**

Size	(1)	(2)
	Number of Firms 2007	% Change Number of Firms 2007-2009
1-49	5,059,512	-3.96
50-499	219,845	-4.98
500+	20,658	-1.95

*Notes:* Number of firms by size class. The first column provides the total number of firms in each firm size class in 2007. The second column provides the percent change in the number of firms between 2007 and 2009 by size class. Source: Business Dynamic Statistics (BDS).

### 3 Financial Constraints and Employment: 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 during 2007-2009 on the entire *universe of firms* in the United States by using confidential micro data from the BLS. Much of the existing literature excludes the vast majority of firms that have fewer than 50 employees. (e.g., Benmelech et al. (2011), Chodorow-Reich (2014)). I construct employment at the firm level by merging all establishments of each firm in the data since it is well known that financial constraints are 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 sector-level external financial dependence measures, I can use all of the firms in the BLS data.

In contrast to the quantitative model in section 4, in which by construction a financial shock is exogenous, the identification of the effect of financial constraints in the data is more challenging because the economy faced multiple shocks during the Great Recession (e.g., increased economic uncertainty and negative demand shocks). It is important to separate the employment-reducing effect coming from the supply of external funds from the employment-reducing effect coming through the demand side and increased economic uncertainty. 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. To control for this possible endogeneity concern, I separate firms into sectors of low and high external financial dependence and employ a difference-in-differences methodology that removes this potential

bias. The EFD measure is constructed following Rajan and Zingales (1998), Kaplan and Zingales (2000), and Cetorelli and Strahan (2006). A reduction in demand that primarily affects small firms thus should affect both low-external-financial-dependence (EFD) and high EFD firms in a similar way. If it is instead the external finance channel that matters for reductions in employment, then one would expect that employment losses during the recession were larger in firms in high EFD sectors. The difference-in-differences estimator differences out the demand effect. I also provide a triple difference estimator that considers the differential growth rates of small versus large firms in high- versus low EFD sector in 2004-2006 versus 2007-2009. Finally, I show that the aggregate demand channel that was emphasized by Mian and Sufi (2012) can not account for my findings on the importance of external financial dependence.

### 3.1 Data

This section briefly describes the dataset and construction of the external financial dependence measure.

Employment data are sourced from the LDB of the QCEW and are available for all establishments in the United States.<sup>6</sup> For each establishment, the LDB data provide information on employment, total wage bill, location information (i.e., county and state), sector, first year of non-zero employment, and employer identification number (EIN). The data are available from 1990 to 2011.<sup>7</sup>

I follow Haltiwanger, Jarmin and Miranda (2013) and Moscarini and Postel-Vinay (2012) in defining firm-level employment growth. In particular, the growth rate of employment  $n$  at firm  $i$  in sector  $j$  in state  $s$  between year  $t$  and  $t - k$  is

$$\% \Delta n_{ijst,t-k} = \frac{n_{ijst} - n_{ijst-k}}{n_{ijst-k}^{\alpha}}, \quad (1)$$

where  $n_{ijst-k}^{\alpha} = \alpha n_{ijst} + (1 - \alpha)n_{ijst-k}$ . A value commonly chosen for  $\alpha$  is 1/2. This definition of the growth rate has several advantages (see Moscarini and Postel-Vinay (2012)). First, the measure is symmetric for positive and negative employment changes. Second, this growth

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<sup>6</sup>The LDB is based on data maintained for tax purposes. It therefore contains all employers with an employer identification number (EIN) and their establishments legally operating in the United States. Not all states make their data available to every external researcher. The states used in the project are AL, AK, AZ, AR, CA, CO, CT, DE, DC, GA, HI, ID, IL, IN, IA, KS, KY, LA, ME, MD, MN, MO, MT, NEB, NV, NJ, NM, ND, OH, OK, PR, RI, SC, SD, TN, TX, UT, VT, VA, VI, WA, WV, and WI.

<sup>7</sup>I use EINs in order to aggregate the employment data to the firm-level. I remove all firms in real estate and financial sectors (SIC codes 6011-6799). I also remove public administration (SIC codes 9111-9721). I also remove Professional Employer Organizations (NAICS 56133). See Appendix C.1 for a more detailed description of the dataset construction.



rate is well defined for entrants and exiters. For entrants it takes the value 2, and for exiters 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, I use the Compustat dataset to construct credit constraint measures. 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), Cetorelli and Strahan (2006), Duygan-Bump et al. (2010), and Shourideh and Zetlin-Jones (2012). 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:

$$EFD_{ij} = \frac{\sum_t CapEx_{ijt} - \sum_t CF_{ijt}}{\sum_t CapEx_{ijt}}. \quad (2)$$

Mature firms are firms that have at least 10 years of data. A value of  $EFD$  smaller than zero indicates that a firm has more cash-flow than capital expenditures and thus tends to have funds available. A value larger than zero indicates that a firm might be financially constrained as capital expenditures exceed available cash-flow. I use the sample period of 1980 to 1996, following Cetorelli and Strahan (2006) and Duygan-Bump et al. (2010). The credit constraint measure for sector  $j$  is chosen to be the median value across all firms in sector  $j$ . The firm-level credit measure then captures the firm's demand for credit rather than effects of credit supply. The financial constraint measure is defined on the SIC-2 level, as is common in the literature (e.g., Duygan-Bump et al. (2010)). I then separate all sectors in the economy into composite sectors of high external financial dependence and low external financial dependence. The high- and low EFD sectors are defined, respectively, as those above and below the median external financial dependence measure.<sup>8</sup>

## 3.2 Empirical Specification

The empirical specification uses employment growth in firm  $i$  in sector  $j$  in state  $s$  from 2007 to 2009 as the dependent variable. Reducing the sample to only one time period mitigates issues of understating standard errors, which was pointed out by Bertrand, Duflo and Mullainathan (2004). A sample with multiple observations per firm over the same period

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<sup>8</sup>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. (2010).

would suffer from strong positive serial correlation, resulting in overestimation of significance levels. I estimate firm-level employment growth as follows:

$$\begin{aligned} \% \Delta n_{ijs}^{2007-2009} = & \beta_0 + \psi_1 \delta_s + \psi_2 \delta_j + \beta_1 \text{small}_{ijs} + \beta_2 \text{young}_{ijs} \\ & + \beta_3 \text{young} * \text{small}_{ijs} + \beta_5 \text{highEFD}_j * \text{young}_{ijs} \\ & + \beta_6 \text{highEFD}_j * \text{small}_{ijs} + \psi_3 X_{ijst} + \epsilon_{ijs}^{2007-2009}, \end{aligned} \quad (3)$$

where  $\text{highEFD}_j$  is an indicator variable that takes the value 1 for sectors of high external financial dependence,  $X_{ijs}$  contains additional control variables,  $\delta_s$  are state fixed effects, and  $\delta_j$  are industry fixed effects. A firm is classified as small (large) if it has fewer than 50 (more than 500) employees in 2007 and is classified as young if it is less than five years old. I divide entrants into the size categories based on their employment size in the data at entry.

### 3.3 Empirical 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 difference-in-differences estimator. Second, I show the results of a triple difference estimator that contrasts the effect of external financial dependence during the financial crisis with that in 2004 to 2006. Third, 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. Finally, I provide multiple robustness checks by adding additional controls including aggregate demand. The appendix provides additional controls such as industry and geographic characteristics.

#### 3.3.1 A Difference-in-Differences Estimator

Generally, small firms tend to be more dependent on bank finance than large firms as they do not have access to bond markets or other sources of external funds. I thus begin by analyzing the differential effect of external financial conditions on small and large firms. Subsequently, I narrow down which firms are driving the differential impact of external financial dependence on small and large firms.

Column (1) in Table 2 shows the results of a simple ordinary least squares regression without fixed effects using firm-level growth rates from 2007:Q4 to 2009:Q3 as described in equation (3). The simple OLS regression indicates that employment in small firms in high EFD sectors grew about 3.8% less than employment in small firms in low EFD sectors. On the other hand, large firms in high EFD sectors grew 8.3% faster than large firms in low EFD

Table 2: **Effect of high EFD on Employment Growth: 2007-2009**

	Employment Growth 2007:4 to 2009:3				
	(1)	(2)	(3)	(4)	(5)
small	0.027*	0.043***	0.045***		-0.085***
	(0.014)	(0.007)	(0.008)		(0.006)
young				0.294***	0.031***
				(0.008)	(0.009)
small high EFD	-0.038**	-0.031***	-0.033***		-0.011
	(0.018)	(0.009)	(0.010)		(0.007)
young high EFD				-0.057***	0.001
				(0.012)	(0.014)
young small					0.274***
					(0.009)
large	-0.035***	-0.017**			
	(0.013)	(0.008)			
young small high EFD					-0.060***
					(0.015)
large high EFD	0.083***	0.017			
	(0.015)	(0.011)			
2-digit SIC, State FE	no	yes	yes	yes	yes
Observations	4042853	4042853	4042853	4042853	4042853

Notes: The dependent variable is the firm-level growth rate between 2007:Q4 and 2009:Q3. Standard errors are in parentheses. Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.

sectors. Column (2) in Table 2 shows that, when fixed effects are included to account for sector and state performance, the central finding remains unchanged qualitatively: employment growth in small firms in high EFD sectors is on average 3.1% lower than for their low EFD counterparts. Large firms in high EFD sectors on the other hand grew faster than low EFD counterparts; however, this finding is insignificant. A positive sign for the interaction between large and high external financial dependence could for example be the result of banks reluctance in lending to small firms, which in turn could have benefited large firms.

To difference out other effects that could have affected small firms differently than large firms, I now examine the double-difference of firm size and external financial dependence:<sup>9</sup>

$$(\hat{\beta}^{small,high} - \hat{\beta}^{large,high}) - (\hat{\beta}^{small,low} - \hat{\beta}^{large,low}) = -0.048^{***}$$

The estimate of  $-0.048$  means that the effect of the recession on small relative to large firms is about (negative) 4.8 percentage points larger in industries with high EFD. Given that the average employment growth rate of firms in the economy is  $-19\%$  (see summary statistics in Appendix C.1), the differential effect of high EFD on small and large firms accounts for an economically significant part of this decline.

The literature highlights the importance of young firms for employment growth. Haltiwanger et al. (2013) find that once firm age is taken into account, firm size loses its significance in explaining employment growth for a sample from 1992 to 2005. Columns (4) and (5) in Table 2 examine the relevance of small and young firms and their interaction with external financial dependence measures during the 2007-2009 recession.

In Column (4) in Table 2, I examine the behavior of young firms during the 2007-2009 recession. Young firms on average grew much faster than the rest of the economy. This difference is driven by entering firms. Exit, on the other hand, is somewhat less skewed towards the young and small. Concurrently, young firms in high EFD sectors grew about 6% slower than their counterparts in low EFD sectors. In Column (5), I examine the interaction of high EFD and small and young firms. Most importantly, the estimation results show that high EFD negatively affected small firms (coefficient:  $-0.011$ ) and most strongly young small firms (coefficient:  $-0.06$ ). In summary, during the 2007-2009 recession, small and young firms in high EFD sectors grew significantly slower than small young firms in sectors less dependent on external financing.

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<sup>9</sup>  $\hat{\beta}^{i,j}$  refers to the conditional growth rate of a firm of size  $i \in \{small, large\}$  in  $j \in \{high, low\}$  external financial dependence sector.

### 3.3.2 A Difference-in-Differences-in-Differences Estimator

In this section I extend the analysis above 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 have for each firm one growth rate for the 2007-2009 period and a growth rate for an equally long period from 2004-2006. The purpose of this experiment 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. 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 that have nothing to do with external finance. It is thus important to express the findings for the 2007-2009 recession relative to this baseline. The difference-in-differences estimator implicitly assumes that the difference in growth rates between low- and high EFD sectors is zero. I select the 2004-2006 period as baseline. Table 3 shows the result of a single regression

Table 3: **Effect of High EFD on Employment Growth 2004-2009**

	Employment Growth (1)
small	0.1323*** (0.007)
small high EFD	0.007 (0.012)
large	0.013 (0.009)
large high EFD	-0.016 (0.013)
small 0709	-0.135*** (0.010)
small 0709 high EFD	-0.062*** (0.017)
large 0709	-0.074*** (0.011)
large 0709 high EFD	0.043*** (0.016)
2-digit SIC, State FE	yes
Observations	8103858

*Notes:* The dependent variable is the firm-level growth rate between 2004:Q4 and 2009:Q3. The regression includes two observations for each firm, one for the 2004-2006 period and one for the 2007-2009 period. Standard errors are in parentheses. Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.

of firm-level employment growth on size and the interactions with high EFD and a financial

crisis dummy. The main finding in Table 3 is that the interactions between size and the financial crisis dummy are negative. Moreover, the interaction of small and high EFD is negative during the financial crisis, while the interaction between large and high EFD is positive. The interaction of size and high EFD have reversed signs in the absence of the financial crisis interaction.

Below I report the triple difference estimation results.

$$\begin{aligned}
& \left( (\hat{\beta}^{small,high} - \hat{\beta}^{large,high}) - (\hat{\beta}^{small,low} - \hat{\beta}^{large,low}) \right)^{2007-2009} \\
& - \left( (\hat{\beta}^{small,high} - \hat{\beta}^{large,high}) - (\hat{\beta}^{small,low} - \hat{\beta}^{large,low}) \right)^{2004-2006} \\
& = -0.105^{***}.
\end{aligned} \tag{4}$$

They show that high EFD reduced employment growth by 10.5 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 4.8 percentage point decline of the difference-in-differences estimator. The relative decline of 10.5 percentage points can thus be interpreted as an upper bound of the effect of financial constraints, while the relative decline of 4.8 percentage points can be interpreted as a lower bound.

### 3.3.3 Controlling for Entry and Exit

Aggregate data as presented in the introduction indicates that the entry and exit margins were of particular importance for employment growth during the financial crisis. The definition of the employment growth rate used in this paper allows me to study further the importance of the extensive margins. In this section I examine only the 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 contrast the results from the sample of continuing firms with the previous results from the entire sample to examine whether controlling for entry and exit changes the estimation results.

Table 4 displays the conditional expected growth rate for small young firms conditional on state and industry fixed effects in the whole sample and in the sample of only continuing firms.<sup>10</sup> The conditional expected growth rate of small young firms is positive in the whole

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<sup>10</sup>The detailed regression results for continuing firms can be found in Appendix Table 14.

Table 4: **Effect of Entry and Exit on Employment Growth: 2007-2009**

	Conditional Expected Growth Rate 2007:4 to 2009:3	
	Whole Sample	Continuing Firms
small young	0.220	0.135
small young high EFD	0.150	0.107
$\Delta$	<b>-.070</b>	<b>-.028</b>
$\Delta\%$	<b>-32%</b>	<b>-21%</b>
2-digit SIC, State FE	yes	yes
Observations	4042853	2821487

Notes: The conditional expected growth rates are calculated using the estimation results in Table 2 for the whole sample and Table 14 in the Appendix for the sample of only continuing firms.

sample as many young and small firms are new entrants, of which each enters with a growth rate of 2. The sample of only continuing firms has a much lower expected conditional growth rate, as all entering and exiting firms are removed. This illustrates that entry is the more important margin for small young firms. In the whole sample, small young firms in high EFD sectors have an expected conditional growth rate that is 7 percentage points lower than the expected conditional growth rate of the small, young firms in low external finance dependent sectors. In the sample of only continuing firms, this difference is only 2.8 percentage points.

### 3.3.4 Controlling for Aggregate Demand

Previously, I argued that the difference in difference methodology should eliminate the effect of other shocks affecting the economy during the Great Recession. However, Mian and Sufi (2012) argue that the aggregate demand channel is responsible for 65% of aggregate job losses during the financial crisis. They argue that aggregate demand was primarily driven by a slump in house prices. Mian, Rao and Sufi (2013) show that counties with a high debt-to-income ratio in 2006 experienced a larger decline in household expenditures during the financial crisis. In this section I therefore add county fixed effects to the analysis to control directly for potential aggregate demand effects. County fixed effects absorb the effect of any shocks that were particular to a specific county. For instance, county fixed effects will capture whether aggregate demand fell particularly in highly levered counties.

The results in Table 5 are close to the baseline results with state-industry fixed effects. In particular, the interaction between high EFD and small (column (1) -0.038), the interaction of young and high EFD (column (3) -0.064) and the interaction of small young and high EFD (column (4), -0.063) are somewhat more negative than their corresponding values in Table 2. The findings thus provide support for the hypothesis that financial constraints were

an important factor for employment growth above and beyond the effects of the aggregate demand channel. The Appendix contains further robustness checks with controls such as pre-recession house price growth, sector and county characteristics, including population size, income, the share of construction in employment, the sector trade share, and the growth rate of population/income between 2002 and 2006.

Table 5: **Effect of High EFD during 2007-2009: County Fixed Effects**

	Employment Growth 2007:4 to 2009:3			
	(1)	(2)	(3)	(4)
small	0.053*** (0.009)	0.054*** (0.008)		-0.077*** (0.006)
young			0.293*** (0.009)	0.034*** (0.010)
small high EFD	-0.038*** (0.019)	-0.039*** (0.010)		-0.015* (0.008)
young high EFD			-0.064*** (0.013)	-0.002 (0.014)
young small				0.275*** (0.012)
large	-0.011 (0.009)			
young small high EFD				-0.063*** (0.016)
large high EFD	0.007 (0.012)			
2-digit SIC FE	yes	yes	yes	yes
county FE	yes	yes	yes	yes
Observations	4042853	4042853	4042853	4042853

*Notes:* The dependent variable is the firm-level growth rate between 2007:Q4 and 2009:Q3. Standard errors are in parentheses. Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.

## 4 Model

In this section I develop a heterogeneous firm model with endogenous firm entry in which a financial crisis leads to a sharp decline in firm entry and most strongly affects small young firms, similar to the finding in the data.



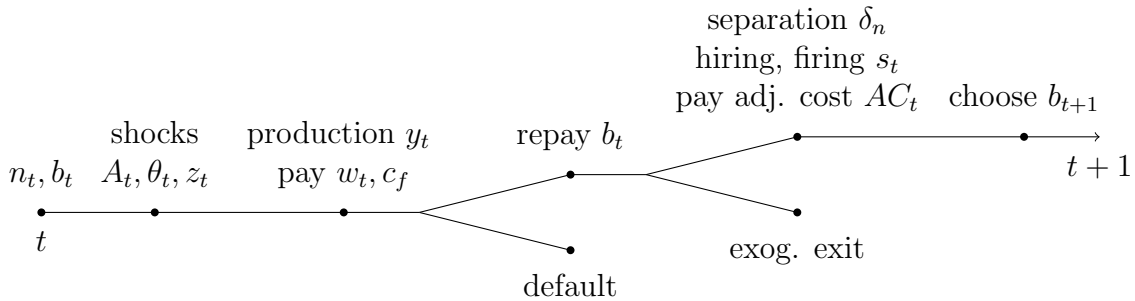
## 4.1 Setup

Time is discrete and indexed by  $t = 1, 2, \dots$ . The model economy has three types of agents: a continuum of households, incumbent firms and potential entrants. I first describe the optimization problem for incumbent firms and then the decision framework for potential entrants, followed by a description of the households problem.

### 4.1.1 Incumbent Firms

There is a continuum of incumbent firms with a production function that has decreasing returns to scale in employment. Incumbent firms are heterogeneous in their individual productivity levels.

Figure 3: **Timing of Decisions for Incumbant Firms**



The timing of decisions for incumbent firms is illustrated in Figure 3: incumbent firms enter period  $t$  with employment stock  $n_t$  and debt  $b_t$ . Employment  $n_t$  is determined a period in advance.

At the beginning of the period, all shocks to aggregate technology  $A_t$ , idiosyncratic technology  $z_t$ , and the recovery rate parameter  $\theta$  are realized. Subsequently, firms choose current period working hours  $h_t$  and produce output  $y_t$ . The production technology of firm  $j$  is given by:

$$y_t = A_t z_t (n_t h_t)^\alpha. \quad (5)$$

For ease of notation, I suppress firm subscript  $j$  in all equations. The firm has two margins of labor adjustment: the intensive margin, hours per employee, which can be adjusted at no cost and the extensive margin, the number of employees, which is subject to an adjustment cost. Firms compensate workers for their labor service by paying wages  $w_t = w(h_t)$ ; they also

pay the fixed cost of operation  $c_f$ .<sup>11</sup> Idiosyncratic and aggregate technology follow AR(1) processes in logs:

$$\log z_{t+1} = \mu_z + \rho_z \log z_t + \sigma_z \epsilon_{t+1}^z \quad (6)$$

$$\log A_{t+1} = \rho_A \log A_t + \sigma_A \epsilon_{t+1}^A, \quad (7)$$

where  $\mu_z$  is a constant and  $\epsilon_{t+1}^A$  and  $\epsilon_{j,t+1}^z$  are iid standard normal random variables. Firms that enter the period with debt meet with the financial intermediary, who then decides if the firm has to go into bankruptcy/default by using an exogenous default rule based on current cash flows. Finally, firms that do not default pay back their debt,  $b_t$ .

To capture the realistic pattern that firms do not grow infinitely wealthy, I impose an exogenous exit rule: Firms reach the end of their life cycle and exogenously exit the economy after production and debt payment with probability  $\pi_d$  (e.g., Khan and Thomas (2013)). Firms that receive this exit signal leave the economy immediately after paying back their debt and pay any remaining profits as dividends to the households. This assumption prevents that all firms in the model become financially unconstrained and also allows it to exhibit a life cycle for firms.

Employment for continuing firms depreciates by a fraction  $\delta_n$  every period. This depreciation is meant to capture that some workers quit every period. Continuing firms then choose the number of workers to hire/fire,  $s_t$ , which then determines next period's employment,  $n_{t+1}$ . Employment thus evolves as follows:

$$n_{t+1} = (1 - \delta_n)n_t + s_t. \quad (8)$$

Firms that adjust their employment pay the associated labor adjustment cost,  $AC_{jt}$ . The adjustment cost function  $AC$  takes a form similar to related work in Bloom (2009), Bachmann (2012), and Berger (2012),

$$AC_t = \lambda y_t + \phi \underbrace{(n_{t+1} - (1 - \delta)n_t)}_{\equiv s_t} \quad \text{if } s_t \neq 0. \quad (9)$$

A fraction of current period output,  $\lambda y_t$ , is lost due to labor adjustment and reflects the disruption effect of labor adjustment.  $\phi s_t$  reflects the partial irreversibility of labor adjustment. One can think of training and disruption (severance payments) in the case of hiring (firing).  $\phi$  is a parameter that determines the adjustment costs, which depend on the

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<sup>11</sup>Model setups that distinguish between hours and number of employees can be found throughout the literature (cf. Burnside, Eichenbaum and Rebelo (1993) and Cooper, Haltiwanger and Willis (2007)).

size of adjustment. Costly labor adjustment is a common assumption and its importance has been documented in empirical work (e.g., Cooper et al. (2007) and Bloom (2009)).

At the end of the period, incumbent firms choose how much debt  $b_{t+1}$  at price  $q_t$  they want to take into the next period. The price  $q_t$  depends on individual firm characteristics. The derivation of the price of debt,  $q_t$ , is discussed in the next paragraph. I impose a non-negativity constraint on dividends that firms have to satisfy. The dividend is:

$$D_t = -c_f + A_t z_t (h_t n_t)^\alpha - w(h_t) n_t - b_t + q_t b_{t+1} - AC_t \geq 0. \quad (10)$$

As there is no tax advantage to debt, firms only take on debt  $b_{t+1} > 0$  to satisfy the non-negativity constraint on dividends,  $D_t \geq 0$ .<sup>12</sup> I assume that firms cannot issue equity. There are various reasons under which incumbent firms can be required to issue debt. Firms can have negative profits because (1) operational fixed costs  $c_f$  are larger than their profits, (2) the productivity realization is low and employment is predetermined, or (3) firms incur labor adjustment cost. Finally, firms that enter the period with debt might have to roll over some debt if profits are not sufficient to repay fully. Firms without debt that cannot satisfy the zero dividend constraint exit the economy. Finally, the economy moves to period  $t + 1$ .

I next describe the price of debt. I employ an exogenous default rule based on the firms' net worth. A similar default rule is used in Gilchrist et al. (2010). Define the net worth of a firm as:

$$nw_t \equiv -c_f + A_t z_t (h_t n_t)^\alpha - w_t(h_t) n_t - b_t. \quad (11)$$

Firms are forced into default by the financial intermediary if  $nw_t < 0$ . Following default, the firm is shut down and exits. Let  $S_t = (A_t, \mu_t)$  denote the aggregate productivity shock and the distribution of firms  $\mu_t$ . This defines a threshold for technology  $\underline{z}$  such that a firm defaults in the next period if  $z_{t+1} < \underline{z}$ . The threshold for technology is determined by the following condition:  $\underline{nw} = -c_f + A_{t+1} \underline{z}(n_{t+1}, b_{t+1}, S_{t+1}) (h_{t+1} n_{t+1})^\alpha - w_{t+1}(h_{t+1}) n_{t+1} - b_{t+1}$ . This implies that there is a threshold for the technology shock  $\underline{\epsilon}$  in period  $t + 1$ , such that  $\underline{\epsilon} \equiv \underline{\epsilon}(n_{t+1}, b_{t+1}, z_t, S_{t+1}) = \log \underline{z}(n_{t+1}, b_{t+1}, S_{t+1}) - \mu_z - \rho_z \log z_t$ . A firm that defaults has to exit and the lender recovers a fraction  $\theta$  of the current period profit.

$$R_t = \max \{ \theta_t (-c_f + y_t - w_t(h_t) n_t), 0 \}, \quad (12)$$

where  $\theta_t$  is the recovery rate in default. A financial shock is modeled as an (unexpected) change in the recovery rate parameter  $\theta_t$ . A decrease in  $\theta_t$  can be interpreted as an increased

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<sup>12</sup> Armenter and Hnatkovska (2011) document that firms today are in fact net lenders.

monitoring cost. A decrease in the recovery rate parameter  $\theta$  means that borrowing on average becomes more expensive and implies a tighter endogenous borrowing constraint for firms.

A firm can only default if it has issued debt. Firms that choose negative debt (assets),  $b_{t+1} < 0$ , save at the risk-free rate and also have to satisfy the non-negativity constraint on dividends. Using the exogenous default rule, the price of debt  $q$  is determined by:

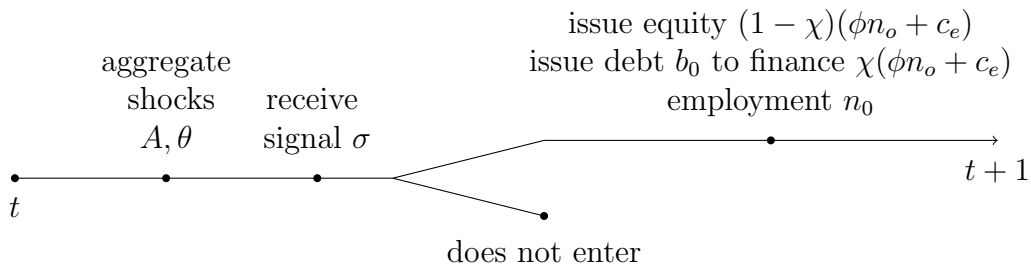
$$q(n_{t+1}, b_{t+1}, z_t; S_t) = \begin{cases} E_t \left[ m(S_t, S_{t+1}) \left( \int_{\underline{\epsilon}}^{\infty} 1 dF(\epsilon_{t+1}) + \int_{-\infty}^{\underline{\epsilon}} \frac{R_{t+1}}{b_{t+1}} dF(\epsilon_{t+1}) \right) \right] & \text{if } b_{t+1} > 0 \\ E_t [m(S_t, S_{t+1})] & \text{if } b_{t+1} \leq 0 \end{cases} \quad (13)$$

I use  $q_t^+$  and  $q_t^-$  to refer to the price of holding positive debt and negative debt (assets), respectively.

The integral in equation 13 can be computed analytically, as documented in the Appendix. The underlying assumption for computing the price of debt above is that the financial intermediary is owned by the household and uses the household's discount factor. In Gilchrist et al. (2010), debt is renegotiated and firms continue to operate at the newly negotiated level of debt.

#### 4.1.2 Potential Entrants

Figure 4: **Timing of Decisions for Potential Entrants**



The timing of decisions for potential entrants is illustrated in Figure 4: At the beginning of each period there is a fixed number of potential entrants  $M$ . One can think of the constant mass of potential entrants in the following way: At each point in time there are a number of (business) ideas that do not depend on the state of the economy. Depending on the quality of the idea and the state of the economy, a fraction of the ideas translate into new

businesses. Potential entrants first observe aggregate shocks to technology  $A_t$  and recovery rate parameter  $\theta$ . Then they receive a signal  $\sigma_t$  about their productivity draw  $z_t$ . The transition between signal and future productivity follows:

$$\log z_t = \mu_s + \rho_s \log \sigma_t + \sigma_s \epsilon_t^s. \quad (14)$$

Upon entry, new firms have to externally finance a fraction  $\chi$  of the startup cost with debt while the remaining fraction  $1 - \chi$  is financed through equity issuance to the households. I assume that entry is the only occasion on which a firm can issue equity. One way to interpret this assumption is that at birth firms rely on a venture capitalist to finance start-up costs but thereafter have to rely on debt finance alone.

The setup of this paper differs from existing work such as Clementi and Palazzo (2013) and Lee and Mukoyama (2012) in an important way: I assume that firms need to externally finance a fraction of the entry cost with debt. The model also differs from existing work on entrepreneurship (such as Buera and Shin (2013) and Bassetto et al. (forthcoming)) because entrepreneurs in their models are risk averse. The implicit assumption underlying the entry framework described in this paper is that entrepreneurs are risk neutral. Consequently, entrepreneurs in the model only maximize the present discounted value of profits.

Each potential entrant compares the value of entering,  $V^e$ , with the cost of entering,  $c_e$ , after receiving signal  $\sigma_t$  about its future productivity. The value of an entrant can be written as:

$$V^e(n_0, b_0, \sigma_t, S_t) = \max_{n_0} (-\phi n_0 + E(m(S_{t+1}, S_t)V(n_0, b_0, z_{t+1}, S_{t+1}) | \sigma_t)), \quad (15)$$

subject to

$$q(n_0, b_0, z_t, A_t, \mu_t)b_0 = \chi(\phi n_0 + c_e). \quad (16)$$

Entrants face the constraint that a fraction  $\chi$  of the cost of entering and hiring has to be financed through debt. The remaining fraction  $1 - \chi$  of the total cost of entry is financed through equity issuance to the households. In the subsequent period, the problem of the entrants is identical to the problem of an incumbent firm. Note that  $V$  is weakly increasing in the idiosyncratic level of productivity  $z_t$ . A higher signal  $\sigma_t$  means that the productivity realization  $z_t$  is likely to be high. This in turn implies that the conditional distribution of  $z_{t+1}$  is decreasing in  $\sigma_t$ . Thus, there exists a threshold  $\sigma^*$  such that:

$$V^e(n_0, b_0, \sigma^*, S_t) = c_e. \quad (17)$$

If the signal is above the threshold ( $\sigma_t \geq \sigma^*$ ) the potential entrant is going to enter and will not enter otherwise. The entry framework adds a selection effect that is novel in the literature: When the costs of borrowing are high, the required threshold signal  $\sigma_t$  to enter is going to be high and the number of entrants will be low. The average productivity of an entrant in this scenario is thus high conditional on its size  $n_0$ .

### 4.1.3 Households

There is a continuum of households of measure one. Households work, consume, and pool their income. Each agent  $i$  has per period preferences:

$$U(c_{it}, H_t) = \log(c_{it}) - \mathcal{I}_{it} \left( \zeta_1 + \zeta_2 \frac{H_t^{1+\vartheta}}{1+\vartheta} \right), \quad (18)$$

where  $\mathcal{I}_{it} = 1$  if the household member is employed and zero otherwise. Each household member is endowed with one unit of time. A household member can work zero hours or can work  $H_t \in [0, 1]$  hours. A fraction  $1 - n$  of households is unemployed and consumes  $c_u$ ; the remaining fraction  $n$  is employed and works  $H_t$  total hours, achieving a consumption level  $c_{n,i}$ , where consumption is allowed to differ across working household members.

The per period utility of the family of households can be written as:

$$U(c_u, c_n, H, n) = (1 - n_t) \log(c_{ut}) + n_t \left( \log(c_{nt}) - \left( \zeta_1 + \zeta_2 \frac{H_t^{1+\vartheta}}{1+\vartheta} \right) \right). \quad (19)$$

Households maximize their utility,

$$\max_{c_{ut}, c_{nit}, H_{it}, n_t, b_{jt+1}} E_t \sum_{t=0}^{\infty} \beta^t U(c_{ut}, c_{nit}, H_{it}, n_t), \quad (20)$$

subject to the budget constraint:

$$(1 - n_t)c_{ut} + n_t c_{nt} + \int q_{jt} b_{jt+1} dj \leq n_t w_t + \int \varrho_{jt} b_{jt} dj + D_t, \quad (21)$$

where  $b_{jt}$  is the amount of debt issued by firm  $j$  in period  $t - 1$  at price  $q_{jt-1}$ . Each unit of debt is redeemed in period  $t$  for  $\varrho_{jt}$ .  $\varrho_{jt}$  captures the loss potentially arising from firm default. The households' inter-temporal decisions are determined by the stochastic discount factor (SDF),  $m(S_{t+1}, S_t) = \beta \frac{\lambda(S_{t+1})}{\lambda(S_t)}$ .  $\lambda$  is the marginal utility of consumption. The household SDF prices all assets. This setup implies that the wage has the following functional form

(see derivation in Appendix B.1):

$$w_t = \frac{1}{\lambda_t} \left( \zeta_1 + \zeta_2 \frac{H_t^{1+\vartheta}}{1+\vartheta} \right). \quad (22)$$

At this wage, the household member is willing to supply any number of hours,  $H_t$ , desired by the firm.<sup>13</sup> Every worker receives a fixed compensation plus an hourly (overtime) premium that depends on the number of total hours worked. Firms take this functional form for the wage as given in their optimization problem. Appendix B.6 defines the equilibrium.

## 4.2 Calibration

The standard approach in the literature (e.g., Bachmann, Caballero and Engel (2013), Khan and Thomas (2013), and Khan (2011)) is to match heterogenous firm models to establishment-level data. As I am interested in firm-level financial constraints, the relevant distribution is the firm-size distribution. Thus, while most of the calibration of the model is standard, a few parameters are different from the literature to account for firms rather than establishments. The period is one year. Table 6 shows the calibration parameters. I set  $\beta = 0.96$ , which corresponds to a 4 percent annual interest rate. The labor share  $\alpha$  is set equal to 0.65. The labor supply elasticity  $\vartheta$  is set to 2.9 following Caballero and Engel (1993). The labor supply parameters  $\zeta_1$  and  $\zeta_2$  are set to match the average employment share in the population of 60 percent and about 30 percent of total available time for hours worked.

Estimates for the separation rates,  $\delta_n$ , vary greatly. JOLTS data from December 2000 to July 2012 imply an annual quit rate of about 19 percent.<sup>14</sup> I thus set  $\delta_n = 0.19$  to capture worker quit rates. I follow Clementi and Palazzo (2013) and assume that the distribution of the signal is Pareto,  $F(\sigma) = (\underline{\sigma}/\sigma)^\varepsilon$ ,  $\varepsilon > 1$  and  $M$  is chosen such that the hours independent part of the equilibrium wage is 6. The parameters  $c_f$  and  $\pi_d$  primarily determine firm exit rates, while  $c_e$  and  $\varepsilon$  determine the relative size of entrants. I set  $\pi_d$  such that 5 percent of firms exogenously exit each year.  $c_f$  is then set to match the average exit rate for firms in BDS data since 1990, of 10 percent. In the model, firm entry and exit rates are identical in the stationary distribution, unlike in the data. For simplicity, I set  $c_e = c_f$ . The size of

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<sup>13</sup>A similar functional form for the wage has previously been used by Cooper, Haltiwanger and Willis (2004) and Cooper et al. (2007) to match the relationship of hours and wages in the data.

<sup>14</sup> While this may sound large, Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2012) use a value for the quarterly quit of 8.8 percent based on findings by Shimer (2005). Berger (2012) also uses a quit rate of 5.7 percent at the quarterly frequency based on JOLTS data. Abowd and Zellner (1985) find that about 3.4 percent of workers exit employment during a typical month between 1972 and 1982. Both Abowd and Zellner (1985) and Shimer (2005) use employment separation as well as quit rates.

Table 6: **Calibration Parameters**

Parameter	Symbol	Value
Discount factor	$\beta$	0.96
Labor Share	$\alpha$	0.65
Employment depreciation rate	$\delta_n$	0.19
Elasticity of disutility of hours	$\vartheta$	2.90
AR(1) coeff. aggregate technology	$\rho_A$	0.859
Std aggregate technology	$\sigma_A$	0.014
AR(1) coeff. idiosyncratic technology	$\rho_z$	0.97
Std idiosyncratic technology	$\sigma_z$	0.20
Fixed operating cost	$c_f$	1.17
Entry cost	$c_e$	1.17
Fraction of lost output if adj.	$\lambda$	0.017
Proportional adj. cost*	$\phi$	0.015
Exogenous death rate	$\pi_d$	0.05
Recovery rate parameter steady state	$\theta$	0.80
External financing fraction at entry	$\chi$	0.30
Pareto Exponent	$\varepsilon$	1.70
Mass of Potential Entrants	$M$	176.84

*Notes:* This table reports the calibration parameters for the model. The proportional adjustment cost parameter is reported as fraction of the annual wage bill.

entrants is determined by the distribution of the signal.  $\varepsilon$  is chosen to match the average size of entrants in the data.

There is a large range of estimates for  $\rho_z$  in the literature. It is the key parameter in determining the firm size distribution. I follow Lee and Mukoyama (2012) and pick  $\rho_z = 0.97$  to approximately match the share of medium and large firms in the economy. For simplicity, the persistence coefficient for the transition between signal and productivity is chosen to be identical to the persistence of idiosyncratic productivity, i.e.,  $\rho(s) = \rho_z$ . The calibration for  $\sigma_z$  is similar to values found by Lee and Mukoyama (2012) as used by Berger (2012) in a related study and smaller than the value used by Bachmann (2012). The parameters for aggregate productivity,  $\rho_A$  and  $\sigma_A$ , follow Khan and Thomas (2008). To obtain a discrete approximation of the two AR(1) processes, I use the method proposed by Rouwenhorst (1995).<sup>15</sup> For computational simplicity  $\theta_t = \theta$  is for simplicity assumed to be 0.8 in the

<sup>15</sup>The quality of approximation remains high even for a highly persistent process, as documented in Kopecky and Suen (2010)



baseline calibration, which corresponds to the average recovery rate reported by the World Bank in the United States. The fixed labor adjustment cost parameter  $\lambda$  is set to 0.017 following Cooper et al. (2004). The labor adjustment cost parameter  $\phi$  is set to 1.5 percent of annual wages.<sup>16</sup> I set the fraction of external funds needed at entry,  $\chi$ , to 0.3. There is only limited information on this value in the data. Data from the U.S. Small Business Administration show that about 50 percent of funds for startups come from credit cards, personal and business loans, and lines of credits. The choice of 30 percent for the fraction of external funds needed at entry is therefore a conservative value.

## 5 Quantitative Results

In this section I describe the numerical results of the model. I first provide details on computation, the price of debt, and the stationary distribution. Then I present impulse response functions for the economy.

### 5.1 Computation

The model requires tracking the distribution of firms over debt and employment, which in principle is an infinitely dimensional object. To simplify the computation, I compute all impulse response functions under the assumption of perfect foresight.<sup>17</sup> In contrast to the algorithm developed by Krusell and Smith (1998), I track the entire distribution on a discrete grid to compute the impulse response functions. Appendix B.2 provides theoretical results that help the computation of the model. The main finding is that in the model, firms only would want to pay dividends if they assign zero probability to being financially constrained in the future. To simplify the computation, I therefore assume that firms never pay dividends unless they exit. This allows me to abstract from the optimal dividend payout policy.<sup>18</sup> Appendix B.7 provides computational details.

### 5.2 Stationary Distribution

Table 7 shows key moments of data and the stationary distribution of the model. Aggregate technology is at its steady state and I assume that  $\theta_t = \theta = 0.8$ . The average firm size in the BDS data is 21.48, which the model matches closely with about 21 employees per firm. The

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<sup>16</sup> This value is similar to the estimate of Bloom (2009) and lower than the estimates of Nickell (1987).

<sup>17</sup>The algorithm is implemented partially in Matlab and Fortran using MEX.

<sup>18</sup> While this assumption sounds strong at first glance, it is not key to any of the results below: In the present setup, a firm never strictly prefers paying dividends over accumulating assets; it either prefers paying no dividends or is at most indifferent.

Table 7: **Data vs. Model**

	(1)	(2)
	Data	Model
Average Employment (Firm)	21.48	20.90
Average Size of Entering Firms	6.75	6.02
Firm Entry Rate	0.101	0.099
Entry Exit Rate	0.086	0.099
Job Reallocation Rate	0.19	0.30
Adjustment Cost/GDP	-	0.05
Default Cost/GDP	-	< 0.01
Entry Cost/GDP	-	< 0.01

Notes: Data Source: Business Dynamic Statistic (BDS) 1990-2011. The data for the inaction rate are taken from Berger (2012). The reallocation rate is taken from Davis, Haltiwanger and Schuh (1996), table 2.1.

average size of entering firms in the data is 6.75, while it is 6.02 in the model. The firm entry rate is 10.4 percent in the data and 9.5 percent in the model. Since the exogenous exit rate is 5 percent in the model, this implies that 4.5 percent of firms endogenously exit through financial distress. In the stationary distribution, the entry and exit rates of the model must be identical; the data, however, show that the 8.6 percent exit rate is somewhat lower than the entry rate. The job reallocation rate in the data is 0.19. The job reallocation rate is not targeted in the calibration and is higher than in the data at 30 percent. The last three rows provide the adjustment cost, default cost, and entry cost relative to GDP in the model. There is no information on the corresponding values in the data. The adjustment costs paid accounts for 5 percent of GDP. This is slightly more than half the adjustment cost in the model of Bachmann (2012). Default cost and entry cost each are below 1 percent of GDP.

In Table 8, I compare the firm size distribution in the data with the model-implied

Table 8: **Firm Size Distribution**

	(1)	(2)	(3)	(4)
	Firm Share		Employment Share	
Firm Size	Data	Model	Data	Model
1-49	0.95	0.94	0.30	0.23
50-499	0.04	0.05	0.21	0.39
500+	0.004	0.004	0.48	0.38

Notes: The table shows the firm size distribution in model and Business Dynamic Statistics (BDS) data.

distribution. The model targets the distribution across size classes and matches the data

well as shown in column (1) and column (2). In the data, 95 percent of firms have fewer than 50 employees, while 94 percent of firms in the model have fewer than 50 employees. Four percent of firms in the data and 5 percent in the model have between 50 and 499 employees. Finally, 0.4 percent of firms in the data and in the model have more than 500 employees. The employment share in the data is difficult to match, as can be seen in column (3) and column (4) in the presence of only a log normally distributed productivity shock. While the employment share of firms for small and large firms is too low in the model, employment in medium-sized firms is too large compared to the data. This will likely lead the model to understate the effect of recessions on small-firm employment as there is higher employment in medium firms than in the data and some medium firms will become small in a recession.

### 5.3 Impulse Response

In this section I first examine the effect of a drop in the recovery rate parameter in case of default,  $\theta$ . I then model a financial crisis as a combination of a financial shock and a temporary reduction in total factor productivity (TFP) and study how the response of the economy differs from that to a TFP shock only. I assume that the economy is at the stationary distribution, computed in general equilibrium, when the shocks hit. Shocks are initially unanticipated and the impulse response functions are computed under perfect foresight and in partial equilibrium.

#### 5.3.1 Temporary Financial Shock

I examine the effect of a temporary reduction in the recovery rate parameter in the case of default. This reduction implies that financial intermediaries will be able to recover only a smaller fraction of firm profits in the case of a default. The parameter determining the recovery rate takes the value  $\theta_t = 0.5$  for 3 years and then immediately returns to its steady state value of  $\theta_t = 0.8$  thereafter. The decline in the recovery rate in the data is however smaller. The “Doing Business Database” of the World Bank states a decline of about 5 percentage points during the financial crisis. Chen (2010) documents that recovery rates for corporate bonds fell during the financial crisis. However, lending to small business is in particular affected not only by the recovery rate but also by declining collateral values of privately owned assets (e.g., houses) that are outside of this model. This is important for start-ups because SBA (2011) documents that start-ups use a variety of private and business sources for funding. The decline in the parameter determining the recovery rate,  $\theta$ , is thus meant to also capture financial conditions outside of the model such as declining collateral

values.<sup>19</sup> The immediate return to the pre-recession level of the recovery rate is chosen to illustrate that the slow recovery is not driven by a gradual return of the shock but, as will become clear later, endogenously through changes in the distribution of firms. The size of the shock is chosen to yield a decline in the number of firms in the economy of about 5 percent, similar to what is observed in the BDS data between 2007 and 2010.

The model's firms follow a life cycle profile: At birth, firms require external finance. According to their productivity, firms then increase employment over time to reach their optimal size. Employment growth of young firms thus depends on the availability of internal or external funds. Finally, when firms reach the end of their life cycle, they exit. A financial shock that increases the costs of external funds then affects financially constrained firms. Unconstrained firms are entirely unaffected by this change. Upon impact, the financial shock affects directly two types of firms in the economy: young firms that are growing and potential entrants. Young firms are exposed to debt as they have to repay the debt taken on at entry, as well as debt they may have taken on to finance expansion of employment and/or the fixed costs of operation and thus have a relative larger debt overhang compared to older firms.<sup>20</sup> Potential entrants are affected by the financial shock as they are required to externally finance a fraction of the entry cost.

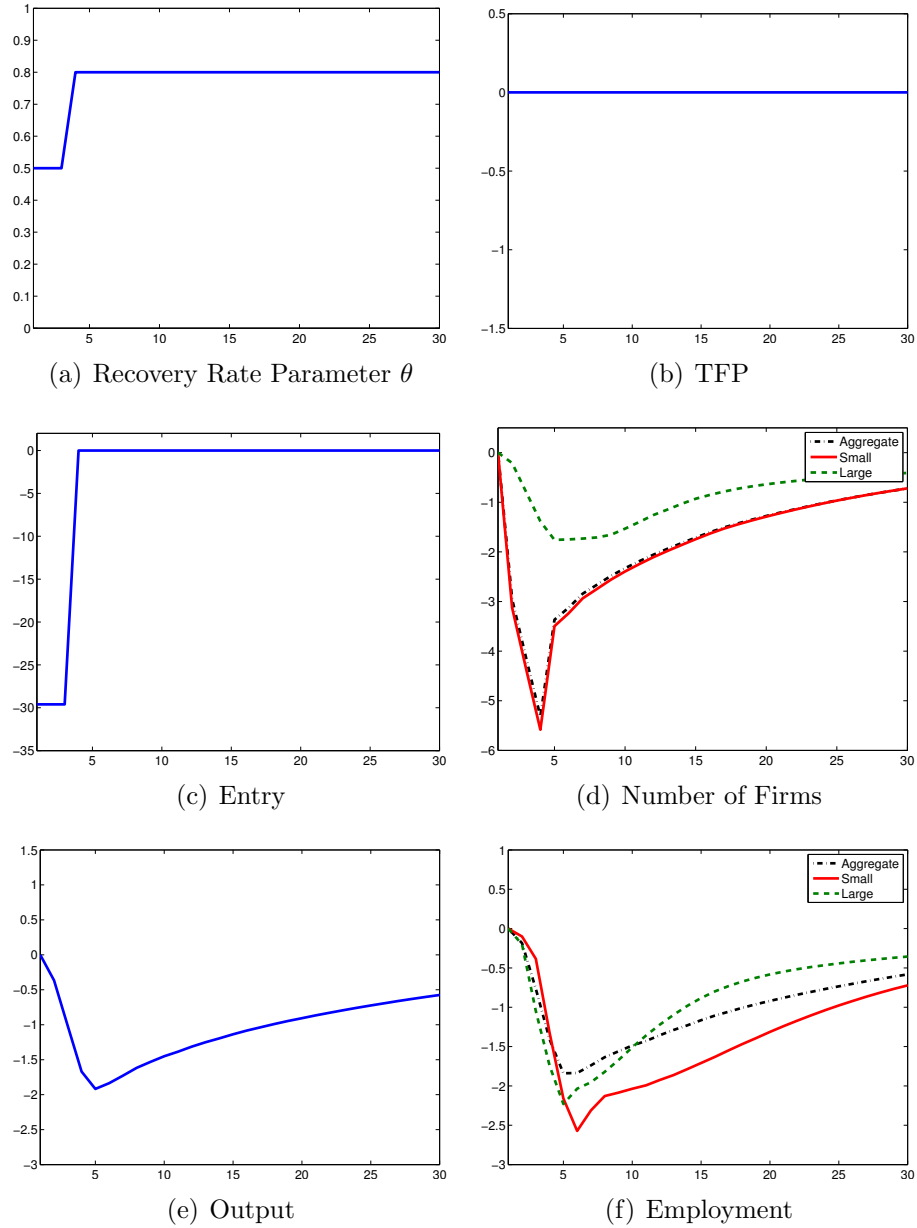
Figure 5 displays the response of the economy to this temporary financial shock. Panel (a) displays the path of the parameter  $\theta$ . Panel (b) shows that aggregate productivity does not change in this experiment. As discussed above, young firms and (potential) entrants are most strongly affected by the financial shock. Entry falls by about 30 percent during the years of the financial shock as shown in panel (c) – in the BDS data entry rates fell 25 percent between 2007 and 2010. Some young firms with debt have difficulties refinancing and/or continuing to expand employment. Panel (d) shows the large decline in the number of firms driven by a decline of small (young) firms of about 5 percent. The number of large firms declines by about 1.8 percent. The decline in economic activity is also reflected in a corresponding 1.9 percent decline in output, panel (e). The decline in the number of firms initially manifests itself in the decline of aggregate employment in panel (f). Employment in small and large firms falls significantly, with small firm employment declining by about 2.5 percent. Aggregate employment falls somewhat less as the decline in large firms implies a smaller decline in employment in medium firms (not shown) as some of the larger firms shrink and become medium-sized. Once the financial shock ends, entry returns to its steady-state

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<sup>19</sup>Alternatively, one could endow the entrepreneurs at birth with a fixed collateral and include the collateral in the net worth condition determining default. A decline in collateral values in such a model would then essentially have a very similar effect on entry.

<sup>20</sup>A negative relationship between loans/asset (loans/ sales) and firm age is in fact also observable in the 2003 Survey of Small Business Finance data.

Figure 5: **Impulse Response: Financial Shock**



*Notes:* The figure shows the response of the economy to a decline in the recovery rate parameter  $\theta_t$  from 0.8 to 0.5 for three years. The vertical axis denotes percentage deviation from the stationary distribution and the horizontal axis denotes years.

level and the number of small firms in the economy increases. However, the entry mechanism in the model created a “missing generation” of entrants – i.e, potential firms that did not enter during the financial shock. While the number of small firms increases immediately after the end of the financial shock, the model results indicate that medium and large firms

that reach the end of their life cycle are only slowly replaced by young fast-growing entrants. Aggregate employment and output start recover only slowly after the financial shock, as it takes many years for the firm size distribution to return to its pre-crisis distribution. The number of small firms displays an immediate initial recovery, although the overall recovery is slow due to the skewed distribution of firms. The model does not predict an overshooting of firm entry after the financial crisis. In the BDS data for the United States, there was no significant recovery or overshooting in firm entry after the financial crisis as of 2012, the last year for which BDS data are available. Given the relative complexity of the model, the simulations are conducted assuming a constant wage and interest rate (as in Bloom (2009)). It is conceptually straightforward, but numerically challenging, to introduce market clearing prices for instance by assuming a representative household. Indeed, in light of Thomas (2002) and Veracierto (2002), one might wonder if the effects wash out in the aggregate entirely. This seems highly unlikely however. Rather, one would expect that wages and risk free interest rates fall in response to tighter credit, which would stimulate labor demand and hence likely somewhat mitigate – but not eliminate – the negative effects on employment and output.<sup>21</sup>

My findings are similar in spirit to the findings in Reinhard and Rogoff (2009a,b). The authors find that economies take significantly longer to recover from a financial crisis (such as the Great Depression) than from ordinary recessions. In the next section I show the response of the economy to a financial crisis which is modeled as a financial shock in combination with a TFP shock. I will show how the recovery differs from a recession, which is caused by a TFP shock alone.

### 5.3.2 Temporary Technology and Financial Shock

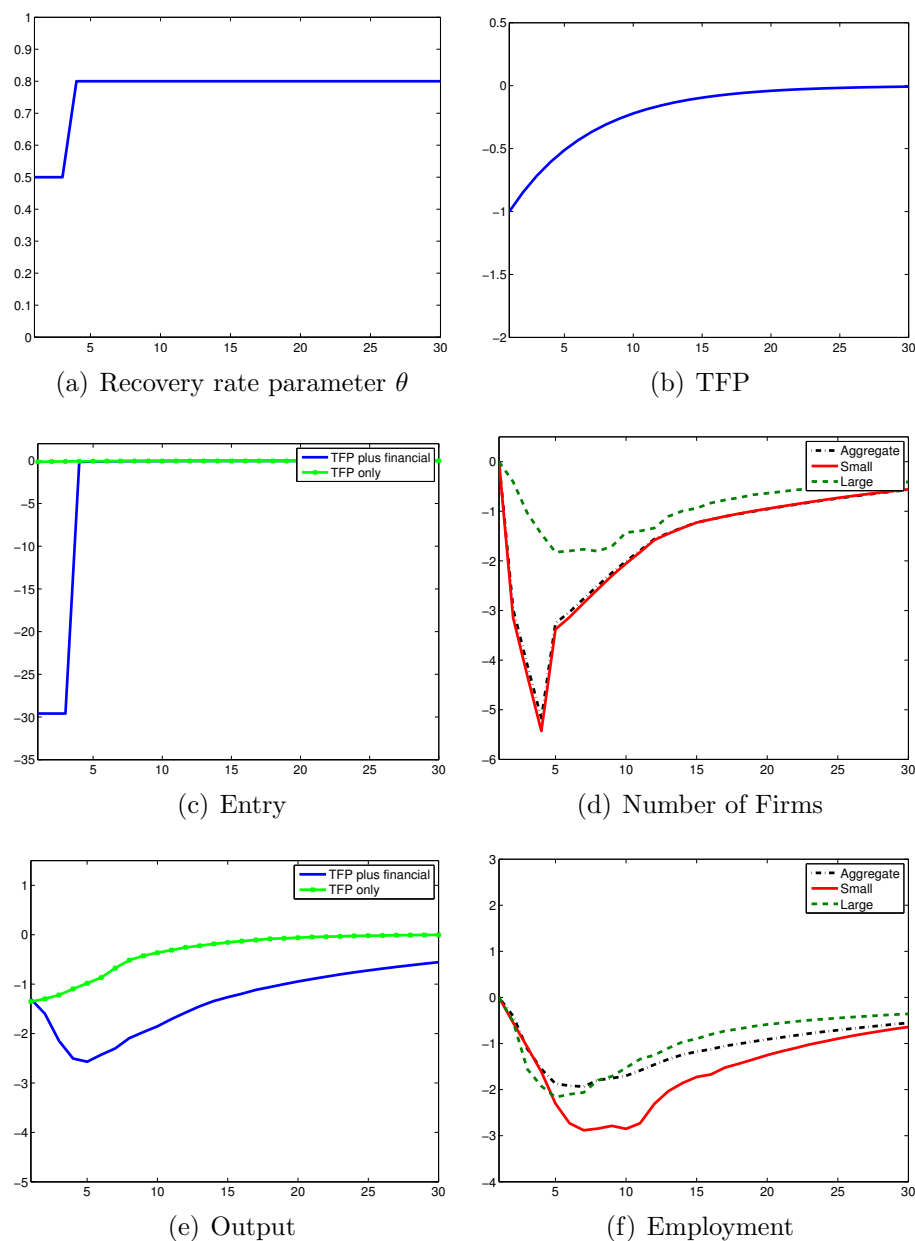
Historically, deep recessions are followed by rapid recoveries unlike the most recent financial crisis. Rapid recoveries are also the prediction of standard RBC models. In this section I examine the recovery after an aggregate technology and a financial shock with the recovery in the presence of a technology shock only.

Figure 6 plots the response of the economy to a persistent decline in total factor productivity (TFP) combined with a three year drop in the parameter that determines the recovery rate in default as in the previous section. The recovery rate parameter,  $\theta$ , drops to 0.5 for three years and then returns to its steady state value, as depicted in panel (a). TFP initially drops by 1 percent and then mean reverts to its steady state, as shown in panel (b). The

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<sup>21</sup>In a related context, Clementi et al. (2014) find that a large decline in entry in their model can generate a slow recovery in general equilibrium. Moreover, researchers examining wage rigidities find evidence for downward rigidity of wages in the Great Recession, e.g., Daly, Hobijn and Lucking (2012), Elsby, Shin and Solon (2013). In addition, the zero lower bound would impose a limit on how much interest rates could fall.

Figure 6: Impulse Response: Financial Crisis



*Notes:* The figure shows the response of the economy to a decline in aggregate technology of 1 percent that subsequently mean-reverts, combined with a decline in the recovery rate parameter  $\theta_t$  from 0.8 to 0.5 for three years. The bright green dotted line in panels (c) and (e) displays the response of the economy in the absence of a financial shock. The vertical axis denotes percentage deviation from the stationary distribution and the horizontal axis denotes years.

decline in aggregate productivity and the financial shock lead to a decline in firm entry of about 30%, as shown in panel (c). The panel also shows that the effect of a TFP shock

alone on entry is minor (less than 1% upon impact). Panel (d) shows that the number of small firms rapidly falls driven by reduced entry. The number of large firms also declines and the total number of firms decreases by about 5%. In comparison to the financial shock alone, the decline in the number of large firms is more persistent but the magnitude in the decline of entry is similar. In panel (e), the behavior of output is, upon impact, similar to a standard RBC model in that output declines by more than TFP does. Output declines for 5 years and at its trough is about 2.6 percent below the pre-crisis level. Compared to the financial shock alone, the recovery is initially somewhat more rapid, which is driven by the mean-reversion of TFP. However, compared to a TFP shock alone, the recovery takes longer. Employment, as shown in panel (f), declines significantly during the financial crisis and recovers only gradually as small firm employment eventually recovers faster than large firm employment. Since the number of employees is predetermined one period in advance, there is no initial decline in employment. Hours worked (not shown), however, decline upon impact of the TFP shock.

In summary, this experiment shows that a reduction in firm entry (through a financial shock) can significantly slow down the recovery compared to a TFP shock alone.

## 6 Conclusion

This paper provides evidence for the importance of financial constraints and firm entry during the Great Recession. I empirically examine, using financial data from Compustat and confidential employment data from the BLS, whether firm financial constraints negatively affected employment growth. I find that, in particular, small and young firms in high external finance dependent sectors exhibited lower employment growth than firms in low external finance dependent sectors. The results further indicate that the entry and exit margins are important in understanding the effects of a financial shock. The empirical findings are robust to the inclusion of controls for aggregate demand.

I also present a heterogenous firm model with financial constraints and firm entry that generates important facts concerning the 2007-2009 recession. The model allows me to study the implication of a financial shock that hits small and young firms especially hard. Firm entry significantly decreases during a financial crisis and the total number of firms falls. The “missing generation” of entrants implies that over time large firms at the end of their life cycle are only slowly replaced by young firms. As a consequence, a slow recovery follows the recession.

The empirical findings and the model results suggest that it is important for policymakers to consider seriously the business conditions for small firms and start-ups in policy design.



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# Firm Entry and Employment Dynamics in the Great Recession

## Appendix – For Online Publication

### **A Additional Stylized Facts**

This section provides additional stylized facts on the change in different measures on lending during the Great Recession.

#### **A.1 Facts on Lending during 2007-2011**

The facts on lending are less well documented than on employment in publicly available data. The first fact is that during the 2007-2009 recession aggregate lending declined. This makes it only the second recession in the last 30 years during which aggregate lending declined.<sup>22</sup> For (large) firms with access to the bond market we know that while credit spreads rose at the onset of the recession they returned rather rapidly to roughly their long run median in 2010. It is also known that large corporation had access to emergency loans from the Federal Reserve Bank at relatively low interest rates.<sup>23</sup> Figure A-1 shows corporate vs non-corporate liability flow from 1986 to today. The graph illustrates that only the Great Recession saw a significant decrease in aggregate liabilities. Furthermore, it is clear that liabilities to the corporate sector fell sharply at the onset of the recession but recovered rapidly. Non-corporate liabilities - which tend to include many small businesses - fell less sharply but more persistently so. Unfortunately the Flow of Funds provide no data on small business lending per se. The exclusive source that documents changes in small business lending is the Call Reports data. From the Call Reports it becomes clear that the total amount of outstanding small business loans increased slightly in 2008 but fell sharply by 4% (6%) in 2009 (2010). Furthermore, many small firms are forced to rely on private sources of credit. As private assets are frequently the only assets a small business or startup has, they utilize consumer credit or home mortgages to finance business expenditures. As the housing sector underwent a major crisis, one can expect that businesses relying on this type of funding are particularly affected in response. The flow of funds provides data on both consumer credit and home mortgages. Figure A-2, panel (a), shows that consumer credit fell during the recession and

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<sup>22</sup>The other being the 1991 recession as documented by Contessi and Francis (2011)

<sup>23</sup>The Federal Reserve Bank made a complete list of borrowers under different programs available at [http://www.federalreserve.gov/newsevents/reform\\_transaction.htm](http://www.federalreserve.gov/newsevents/reform_transaction.htm).

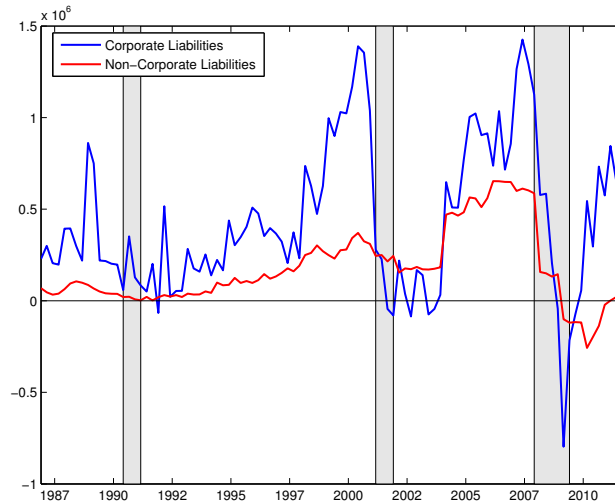
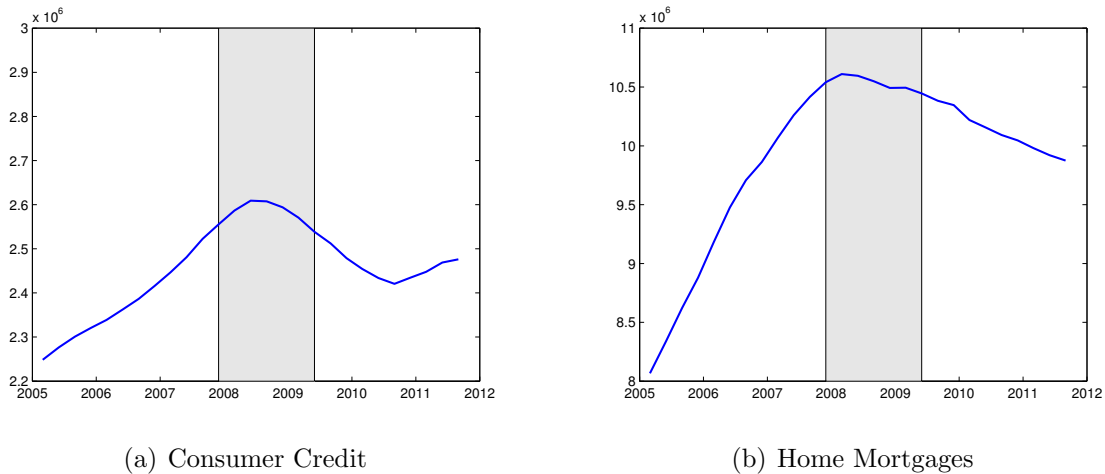


Figure A-1: **Corporate and Non-Corporate Liabilities**

Notes: Flow of corporate and non-corporate liabilities from 1987 Q1 to 2011 Q3 in thousand dollars Gray shaded areas mark NBER recessions. Source: Flow of Funds.

figure , panel (b) confirms that home mortgages have been on a steady decline since 2008. Ivashina and Scharfstein (2010) provide empirical evidence for a large fall in lending. They find that the dollar lending volume in the fourth quarter of 2008 declined 47% relative to the prior quarter.



(a) Consumer Credit

(b) Home Mortgages

Figure A-2: **Consumer Lending**

Notes: Consumer Credit and Home Mortgages (Levels) in thousand U.S. Dollars. Grey Shaded area marks NBER recession of 2007-2009. Source: Flow of Funds

## B Quantitative Model Appendix

### B.1 Households Optimality Conditions

$$U(c_u, c_n, H, n) = (1 - n_t) \log(c_{ut}) + n_t \left( \log(c_{nt}) - \left( \zeta_1 + \zeta_2 \frac{H_t^{1+\vartheta}}{1+\vartheta} \right) \right) \quad (\text{A-1})$$

subject to the budget constraint

$$(1 - n_t)c_{ut} + n_t c_{nt} + \int q_{jt} b_{jt+1} dj \leq n_t w_t + \int \varrho_{jt} b_{jt} dj + D_t, \quad (\text{A-2})$$

Let  $\lambda$  denote the multiplier on the budget constraint. The first order conditions with respect to  $c_{ut}$  and  $c_{nit}$  imply perfect risk sharing in consumption, that is

$$1/c_{ut} = \lambda_t \quad (\text{A-3})$$

$$1/c_{nit} = \lambda_t \quad \forall i \quad (\text{A-4})$$

It follows that  $c_{ut} = c_{nit}$ .  $\lambda$  denotes the marginal utility of consumption. Finally, the first order condition with respect to  $n_t$  is

$$-\log(c_{ut}) + \log(c_{nt}) - \left( \zeta_1 + \zeta_2 \frac{H_t^{1+\vartheta}}{1+\vartheta} \right) = -\lambda_t (w - c_{nt} + c_{ut}) \quad (\text{A-5})$$

This again implies that the wage for the worker has to equal

$$w = \frac{1}{\lambda} \left( \zeta_1 + \zeta_2 \frac{H_t^{1+\vartheta}}{1+\vartheta} \right) \quad (\text{A-6})$$

### B.2 Theoretical Results on Dividends

This section describes two propositions regarding the dividend payment policy pursued by incumbent firms in the model. The propositions show the dividend payout policy that firms that issue debt,  $b_{t+1} > 0$  and firms that hold assets,  $b_{t+1} \leq 0$  pursue.

**Proposition 1.** *It is optimal that continuing firms with positive debt holdings,  $b_{t+1} > 0$ , do not pay dividends unless they assign a zero probability to a binding dividend constraint in the future.*

*Proof.* See Appendix B.3. □

This finding is similar to Caggese (2007) and Khan and Thomas (2013). The intuition

is simple: Since the price of debt is less (or equal) to the stochastic discount factor of firms, debt is on average costly and thus firms are better off by paying back their debt. That is, a dollar inside the firm is worth more than a dollar outside the firm. Proposition 2 provides a similar statement to Proposition 1 for firms with asset holdings  $b_{t+1} \leq 0$ .

**Proposition 2.** *Continuing firms that choose positive asset holdings,  $b_{t+1} < 0$ , only consider paying dividends if they assign zero probability to having a binding dividend constraint in the future.*

*Proof.* See Appendix B.3. □

The intuition for this proposition is somewhat less straightforward: Firms want to avoid to be in the situation in the future that their dividend constraint might be binding and thus want to save and pay zero dividends. As firms and households share the same stochastic discount factor, firms are at most indifferent between paying dividends and saving. The results are important for the following reason: It matches the realistic fact that start-ups are financially constrained and over time accumulate assets such they eventually become unconstrained. Firms save for precautionary reasons. In aggregate firms in the model are net lenders, similar to evidence provided by Armenter and Hnatkowska (2011).

## B.3 Proofs

### B.3.1 Proof of Proposition 1

*Proof.* This can easily be shown attaching an explicit multiplier to the non-negativity dividend constraint. Denote this multiplier  $\mu$ . Under the assumption of exogenous default  $\pi_d > 0$  the first order conditions change slightly and the first order condition with respect to  $b'$  then becomes:

$$(1 + \mu) \left( q + \frac{\partial q}{\partial b'} b' \right) + E \left( m \left( \int_{\underline{\epsilon}}^{\infty} \frac{\partial V^{0'}}{\partial b'} dF(\epsilon') - V^{0'}(\underline{\epsilon}) f(\underline{\epsilon}) \frac{\partial \underline{\epsilon}}{\partial b'} \right) \right) = 0 \quad (\text{A-7})$$

We know that at  $\underline{\epsilon}$  the firm is exactly indifferent between defaulting and not defaulting. As the firm value in default by assumption is zero, it has to be true that  $V^{0'}(\underline{\epsilon}) = 0$ .

The envelope theorem implies

$$\begin{aligned} \frac{\partial V^0}{\partial b} &= \int_0^B \frac{V^1}{\partial b} \frac{1}{B} d\epsilon \\ \frac{V^1}{\partial b} &= -(1 + (1 - \pi_d)\mu) \end{aligned} \quad (\text{A-8})$$



and thus

$$\begin{aligned} (1 + \mu) \left( q + \frac{\partial q}{\partial b'} b' \right) &= E \left( m \left( \int_{\underline{\epsilon}}^{\infty} (1 + (1 - \pi_d) \mu') dF(\epsilon') \right) \right) \\ (1 + \mu) \left( q + \frac{\partial q}{\partial b'} b' \right) &= E (m(1 - F(\underline{\epsilon})) + m(1 - \pi_d) \mu' (1 - F(\underline{\epsilon}))) \end{aligned} \quad (\text{A-9})$$

We know the price of debt  $q$  from above is

$$q(A', z, n', b', \mu) = E \left[ m(s, s') \left( 1 - F(\underline{\epsilon}) + \int_{-\infty}^{\underline{\epsilon}} \frac{\max \{ \theta (y' - w'(h') n'), 0 \}}{b'} dF(\epsilon') \right) \right] \quad (\text{A-10})$$

but  $\partial q / \partial b'$  needs to be determined using the Leibnitz rule.

$$\frac{\partial q}{\partial b'} b' = E \left( m \left( - \int_{-\infty}^{\underline{\epsilon}} \frac{\max \{ \theta (y' - w'(h') n'), 0 \}}{b'} dF(\epsilon') - \left( 1 - \frac{\max \{ \theta (y' - w'(h') n'), 0 \}}{b'} \right) b' f(\underline{\epsilon}) \frac{\partial \underline{\epsilon}}{\partial b'} \right) \right) \quad (\text{A-11})$$

We know that  $\partial \underline{\epsilon} / \partial b' > 0$ . Now we can combine the equations above and after some rewriting obtain:

$$\mu \left( q + \frac{\partial q}{\partial b'} b' \right) = E (m(1 - \pi_d) \mu' (1 - F(\underline{\epsilon}))) \quad (\text{A-12})$$

This implies that unless agents put probability 1 on  $\mu' = 0$  that  $\mu \neq 0$  when debt holding is positive. Thus the dividend constraint has to bind at all times unless the firm exogenously exits.  $\square$

### B.3.2 Proof of Proposition 2

*Proof.* The optimality condition for firms with positive asset holdings,  $b' < 0$ , is somewhat different from the above since firms with positive asset holdings are not subject to the default constraint in terms of  $nw$ . Furthermore, they receive a price  $q_t = E(m)$  for each unit of savings.

$$(1 + \mu)q + E \left( m \frac{\partial V^0}{\partial b'} dF(\epsilon') \right) = 0 \quad (\text{A-13})$$

The envelope theorem implies

$$\begin{aligned}\frac{\partial V^0}{\partial b} &= \int_0^B \frac{V^1}{\partial b} \frac{1}{B} d\varepsilon \\ \frac{V^1}{\partial b} &= -(1 + (1 - \pi_d)\mu)\end{aligned}\tag{A-14}$$

and thus

$$\begin{aligned}(1 + \mu)q &= E(m(1 + (1 - \pi_d)\mu')) \\ (1 + \mu)E(m) &= E(m + m(1 - \pi_d)\mu')\end{aligned}\tag{A-15}$$

Thus,  $\mu = 0$  if and only if firms assign zero probability to the event that the dividend constraint will be binding next period. Consequently, firms with positive asset holdings are at most indifferent to pay dividends as they use the same discount factor as the households.  $\square$

## B.4 Incumbent Optimization

The firm's problem can be written recursively: Let  $V^0$  denote the value function of a firm that is not defaulting today. The firm's problem can be divided into subproblems. The firm knows that with probability  $\pi_d$  it is not going to survive until next period and with probability  $(1 - \pi_d)$  it survives and has value  $V^1$ . Further, let  $S_t$  summarize the aggregate state variables of the economy, aggregate productivity  $A_t$ , and the distribution of firms,  $\mu_t$ . Thus, today's value of the firm is:

$$\begin{aligned}V^0(n_t, b_t, z_t; S_t) &= \pi_d \max_h (-c_f + A_t z_t (h_t n_t)^\alpha - w_t (h_t) n_t - b_t) \\ &\quad + (1 - \pi_d) V^1(n_t, b_t, z_t; S_t).\end{aligned}\tag{A-16}$$

Firms that do not default in period  $t$  and survive can choose between adjusting or not adjusting their employment. Thus, I can use two different value functions for firms that do not adjust employment  $V^{1,n}$  and firms that do adjust employment  $V^{1,a}$ :

$$V^1(n_t, b_t, z_t; S_t) = \max \{V^{1,n}(n_t, b_t, z_t; S_t), V^{1,a}(n_t, b_t, z_t; S_t)\}.\tag{A-17}$$

I then distinguish between firms that choose positive debt  $b_{t+1} > 0$  and firms that choose negative debt  $b_{t+1} < 0$ . Firms with positive debt obtain external funds at price  $q_t^+$ . Firms with negative debt (positive assets) save at the risk-free rate  $q_t^-$  and face zero probability of

default.

First, consider the firms that do not adjust employment today:

$$V^{1,n}(n_t, b_t, z_t; S_t) = \max \{V_{b_-}^{1,n}(n_t, b_t, z_t; S_t), V_{b_+}^{1,n}(n_t, b_t, z_t; S_t)\}. \quad (\text{A-18})$$

The optimization problem for the firm that does not adjust employment and chooses  $b_{t+1} > 0$  takes the following form:

$$\begin{aligned} V_{b_+}^{1,n}(n_t, b_t, z_t; S_t) = & \max_{h_t, b_{t+1} > 0} \left\{ -c_f + A_t z_t (h_t n_t)^\alpha - w_t(h_t) n_t + q_t^+ b_{t+1} - b_t \right. \\ & \left. + E_t \left( m(S_t, S_{t+1}) \int_{\underline{\epsilon}}^{\infty} V^0(n_t(1-\delta), b_{t+1}, z_{t+1}; S_{t+1}) dF(\epsilon') \right) \right\}, \end{aligned} \quad (\text{A-19})$$

subject to the non-negativity constraint in dividends, equation (10), and the price of debt, equation (13). I assume that firms and households share the same discount factor  $m(S_t, S_{t+1})$ . Borrowing is costly if firms face a non-zero probability of default, and in the absence of a tax advantage of debt, firms have no incentive to take on debt. Thus firms only take on debt to satisfy the non-negativity dividend constraint. For a firm that chooses  $b_{t+1} < 0$ , the Bellmann equation becomes:

$$\begin{aligned} V_{b_-}^{1,n}(n_t, b_t, z_t; S_t) = & \max_{h_t, b_{t+1} \leq 0} \left\{ -c_f + A_t z_t (h_t n_t)^\alpha - w_t(h_t) n_t + q_t^- b_{t+1} - b_t \right. \\ & \left. + E_t \left( m(S_t, S_{t+1}) V^0(n_t(1-\delta), b_{t+1}, z_{t+1}; S_{t+1}) \right) \right\}, \end{aligned} \quad (\text{A-20})$$

subject to equations (10) and (13).

Second, the problem of a firm that decides to adjust employment today can also be expressed as:

$$V^{1,a}(n_t, b_t, z_t; S_t) = \max \{V_{b_-}^{1,a}(n_t, b_t, z_t; S_t), V_{b_+}^{1,a}(n_t, b_t, z_t; S_t)\}. \quad (\text{A-21})$$

The firm that does choose to adjust its employment and chooses  $b_{t+1} > 0$  faces the following problem:

$$\begin{aligned} V_{b_+}^{1,a}(n_t, b_t, z_t; S_t) = & \max_{s_t, h_t, b_{t+1} > 0} \left\{ -c_f + A_t z_t (h_t n_t)^\alpha - w_t(h_t) n_t + q^+ b_{t+1} - b_t \right. \\ & \left. - AC_t + E_t \left( m(S_t, S_{t+1}) \int_{\underline{\epsilon}}^{\infty} V^0(n_t(1-\delta) + s_t, b_{t+1}, z_{t+1}; S_{t+1}) dF(\epsilon) \right) \right\}, \end{aligned} \quad (\text{A-22})$$

subject to equations (10) and (13), and the labor adjustment costs as defined in equation

(9). An adjusting firm that chooses  $b_{t+1} < 0$  faces the following Bellman equation:

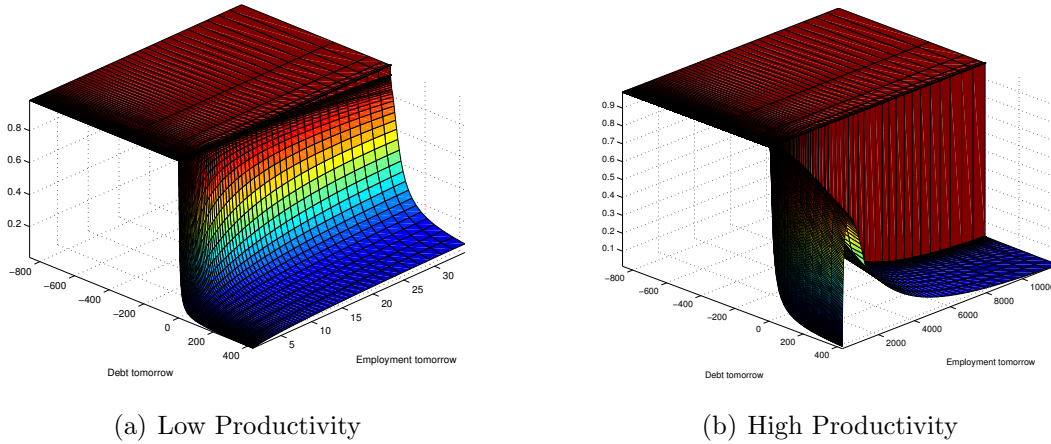
$$V_{b^-}^{1,a}(n_t, b_t, z_t; S_t) = \max_{s_t, h_t, b_{t+1} \leq 0} \left\{ -c_f + A_t z_t (h_t n_t)^\alpha - w_t(h_t) n_t + q_t^- b_{t+1} - b_t - AC_t + E_t(m(S_t, S_{t+1}) V^0(n_t(1-\delta) + s_t, b_{t+1}, z_{t+1}; S_{t+1})) \right\}, \quad (\text{A-23})$$

subject to equations (10) and (13), and the labor adjustment costs as defined in equation (9). The hours choice of the firm is static and solved every period. In the next section I describe the optimization problem of potential entrants.

## B.5 Price of Debt

Figure A-3, panel (a) depicts the price of debt/assets for a low productivity firm. The price of debt depends on the future employment choice, as well as the debt choice. Panel (a) shows that a low productivity firm can only obtain a low interest rate at low values of debt and at low levels of employment. Figure A-3, panel (b) shows the price of debt for a higher productivity firm. A higher productivity firm has the ability to take on a significant amount of debt with much larger employment stock.

Figure A-3: Price of Debt



## B.6 Recursive Equilibrium

A recursive equilibrium is a set of functions:

$$\{w, p, V^1, \Gamma, C, q, n^h, h^h, N, H\} \quad (\text{A-24})$$

that solve households', firms', and financial intermediary problems, as well as clears the good, labor, and bond markets. In particular, it satisfies the following set of conditions:

1. *Households* Taking  $w$  as given, the households' labor supply  $h^h$  and  $n^h$ , consumption  $c_u^h, c_n^h$  satisfy the households optimality conditions and their budget constraint.
2. *Incumbants* Taking  $w, p, q, \Gamma$  as given,  $V^1(n, b, z, A, \mu)$  solves (A-17). The implied policy functions are  $H(n, b, z, A, \mu)$ ,  $N(n, b, z, A, \mu)$ , and  $B(n, b, z, A, \mu)$ .
3. *Financial Intermediary* The financial intermediary determines the optimal bond price  $q(n, b, z; A, \theta, \mu)$  using equation (13), taking the household stochastic discount factor as given.
4. *Goods Market Clearing* Aggregate consumption plus adjustment cost and bankruptcy cost equal aggregate output:

$$\begin{aligned}
C(n, b, z; A, \mu) = & \int Az (H(n, b, z; A, \mu) N(n, b, z; A, \mu))^\alpha d\mu - \\
& \int AC(n, b, z; A, \mu) \mathcal{J}(N(n, b, z; A, \mu) - n(1 - q)) (1 - \pi_d) d\mu - \\
& \int \mathcal{J}(nw(n, b, z; A, \mu) \leq \bar{n}\bar{w}) \varrho d\mu - \int c_e d\mu^e, \tag{A-25}
\end{aligned}$$

where  $\mathcal{J}(x) = 0$  if  $x = 0$  and 1, otherwise. The second-to-last term captures the loss of default, while the last term captures the cost of firm entry.

5. *Labor Market Clearing*

$$\begin{aligned}
\int_0^1 n_{it}^h di &= \int N(n, b, z, \varepsilon; A, \theta, \mu) d\mu \\
\int_0^1 h_{it}^h di &= \int H(n, b, z; A, \theta, \mu) d\mu
\end{aligned}$$

6. *Measure of Entrants*

$$\mu_t^e = M \int_S \int_{\mathcal{B}} dQ(s) dH(z'|\sigma), \tag{A-26}$$

where  $\mathcal{B} = \{r \text{ s.t. } V^e(n_0, b_0, \sigma, S) \geq c_e\}$ . The number of entrants is determined by the mass of potential entrants  $M$  and the fraction of firms for which the value of entering is larger than the cost of entering.

7. *Model Consistent Dynamics* The evolution of the distribution of firms follows

$$\mu_{t+1} = \Gamma(A_t, \mu_t, \mu_t^e), \tag{A-27}$$

where  $\mu_t$  is the distribution of firms over employment, debt, and idiosyncratic technology.

## B.7 Computation

Instead of solving for the value function  $V(n, b, z, S)$  I solve for the value function  $V(n, \tilde{b}, z, S)$  where  $\tilde{b} = b/n$ . This helps in constructing a sensible grid for debt as the debt capacity of a firm is proportional to employment. I can then derive the implied policy functions.

### B.7.1 Computation of the Model: Stationary Distribution

The policy functions  $n' = g(n, b, A, z)$ ,  $b' = h(n, b, A, z)$  as well as the exit and default policy that, summarized in  $d = d(n, b, A, z)$  can be obtained using the result from the value function iteration above. Let  $\mu(n_0, b_0, z_0)$  measure the proportion of firms with employment  $n_0$ , net assets  $b_0$ , and idiosyncratic technology  $z_0$ . The stationary distribution  $\mu(n, b, A, z)$  can be determined by iterating on the following equation:

$$\mu_{t+1}(n_0, b_0, z_0) = \int \mathbf{1}_{g(n,b,Z)} \mathbf{1}_{h(n,b,z)} \mathbf{1}_{d(n,b,z)} Q(n, b, z) (\mu_t(dn, db, dz) + \mu_t^e(dn, db, dz)) \quad (\text{A-28})$$

where  $\mu$  is a measure on the measurable space  $(N \times B \times Z, \mathcal{N} \times \mathcal{B} \times \mathcal{Z})$ . Script letters denote Borel  $\sigma$ -algebras that are generated by subsets of  $N \times B \times Z$ .

Note that I start iterating from a uniform distribution as an initial guess. Furthermore,  $Q$  denotes the transition matrix implied by the exogenous technology process  $z$  and the policy functions. As  $Q$  is finite dimensional it is important to note that I discretize the state variable on a finer grid than used for the value function iteration. Since policy functions are interpolated their results may not fall on the fine grid. In this case I proceed as follows: Let  $g(n, b, z)$ ,  $h(n, b, z)$  be the implied policy functions. I find the grid points closest to the policy such that  $n_i < g(n, b, z) < n_{i+1}$  where  $\{n_i\}$  are on the fine grid.<sup>24</sup> Then I assume that the firm chooses  $n_i$  with probability  $\frac{n_{i+1}-g(n,b,z)}{n_{i+1}-n_i}$  and the firm chooses  $n_{i+1}$  with probability  $1 - \frac{n_{i+1}-g(n,b,z)}{n_{i+1}-n_i}$ . Similarly for  $h(n, b, z)$  I find  $b_i < h(n, b, z) < b_{i+1}$ , the firm chooses  $b_i$  with probability  $\frac{b_{i+1}-h(n,b,z)}{b_{i+1}-b_i}$  and  $b_{i+1}$  with probability  $1 - \frac{b_{i+1}-h(n,b,z)}{b_{i+1}-b_i}$ . This method is also suggested by Rios-Rull (2001) and has previously been used by Gourio and Miao (2010)

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<sup>24</sup>It turns out that the choice of the fine grid for employment is very important in this framework. I thus choose the grid to include all the points that satisfy  $\bar{n}(1 - \delta)^i$ . The reason is simply that by including these points it is possible for every allocation of employment today, that each firm can choose the level of next period employment that would basically allow for not adjusting the employment.

### B.7.2 Computation with Entry: Fixed Mass of potential Entrants

1. Make a guess for the mass of potential entrants  $M$ . Firms take the functional form of the wage as given, i.e.  $w(h) = \frac{1}{\lambda_t} \left( \zeta_1 + \zeta_2 \frac{H^{1+\vartheta}}{1+\vartheta} \right)$ . Fix the hours independent part of the wage to 6. Compute the firms value function of the incumbent  $V$  through value function iteration. I use a finer grid for future employment,  $n_{t+1}$  than for current employment  $n_t$ . For each state today and choice of employment tomorrow I compute the required value of debt tomorrow  $b_{t+1}$  that results from the non-negativity constraint on dividends. The value function and the price of debt  $q$  is approximated through piecewise cubic splines. This allows me to accurately evaluate off-grid choices.
2. Compute the value of entering given a signal  $s$  taking into account that the transition matrix for potential entrants is the same as the transition matrix for incumbents, choosing the optimal employment level, and taking the financial constraints into account. Since the value of the incumbent is weakly increasing in idiosyncratic TFP there exists a unique threshold  $s^*$ . Given a mass of potential entrants  $M$  actual mass of entrants becomes  $N = M(1 - F(s^*))$ .
3. Given the mass of entrants and policy functions from above compute the stationary distribution  $\mu^*$ . Now it is possible to compute aggregate variables like consumption. Using the result for consumption compute the marginal utility of consumption  $\hat{\lambda}$ 
  - If the implied marginal utility of consumption is too high,  $\hat{\lambda} > \lambda^*$ , increase  $M$ , otherwise
  - If the implied marginal utility of consumption is too low,  $\hat{\lambda} < \lambda^*$ , decrease  $M$ .

Start over and repeat until convergence.

### B.7.3 Computation of the Model: Transitional Dynamics under Perfect Foresight

Suppose the economy start at the stationary distribution associated with a particular financial state  $\theta_0$ . This section highlights the computation in general equilibrium, the partial equilibrium computation is simpler in that there is no need to update the guess for the marginal utility of consumption as prices are assumed to be fixed at the initial steady state level. Suppose that the economy is subject to a shock which permanently changes the financial state  $\theta_1$  (the computation goes through one for one if the shock is only temporary). Suppose that for  $t > T$ ,  $T$  large enough, the economy reaches its new steady state. The

following steps then explain how to solve for the transitional dynamics implied by the financial shock with path  $\{\theta_t\}_{t=0}^T$ . The exposition here follows Khan (2011), Gourio and Miao (2010) and Guerrieri and Lorenzoni (2010). The computation of the first two steps follows the outline discussed in Appendix B.7.2.

1. Compute the initial steady state corresponding to financial friction state  $\theta_0$ . The steady state is characterized by aggregate employment  $N_0^*$ , aggregate net debt  $B_0^*$ , the firms value function  $V_0^*$ , the value of the entering firm  $V_0^e$ , and a cross sectional distribution of firms denoted by  $\mu_0^*(n, b, z)$ .
2. Compute the final steady state corresponding to financial friction state  $\theta_1$ . The steady state is characterized by aggregate employment  $N_1^*$ , aggregate net debt  $B_1^*$ , the firms value function  $V_1^*$ , the value of the entering firm  $V_1^e$ , and a cross sectional distribution of firms denoted by  $\mu_1^*(n, b, z)$ . For temporary shocks the initial and final steady states are identical.
3. Guess a path of marginal utility of consumption  $\{\lambda_t\}_{t=0}^T$ . The guess for the marginal utility of consumption  $\lambda_t$  implies a guess for the wage function  $w_t(h) = \frac{1}{\lambda_t} \left( \zeta_1 + \zeta_2 \frac{H^{1+\vartheta}}{1+\vartheta} \right)$  and  $r_t = \frac{\lambda_t}{\beta \lambda_{t+1}}$ .
4. Given the path of  $\{\lambda_t\}_{t=0}^T$  solve the firms value function backwards starting with period  $T - 1$  and using the fact that  $V_T = V_1^*$ . Given this information it is straightforward to compute the value function  $V_{T-1}$  and the value function of the entering firms  $V_{T-1}^e$ . Compute the value function for each point in the  $t = T - 1, \dots, 1$
5. For each point in time  $t = T - 1, \dots, 1$  compute the signal threshold  $s_t^*$  such that

$$V_t^e(n_0, b_0, s_t^*, S) = c_e \tag{A-29}$$

for each optimal choice of  $n_0$  and corresponding  $b_0$ , which results from the financial constraint.

6. For all  $t$  compute the mass of new entrants using the signal threshold form above, i.e.  $N_t = M_t(1 - F(s_t^*))$ .
7. Derive aggregate values for consumption  $C_t$ , employment  $N_t$ , output  $Y_t$  and compute the true marginal utility of consumption  $\lambda_t^{true}$ . Update the guess for  $\lambda_t^{k-1}$  in iteration  $k - 1$  for iteration  $k$  and recompute the value functions until the marginal utility of



consumption remains unchanged.

$$\lambda_t^k = \lambda_t^{k-1} - d(\lambda_t^{k-1} - \lambda_t^{true}) \quad (\text{A-30})$$

where  $0 < d < 1$ .

## C Empirical Model Appendix

### C.1 Dataset Construction and Summary Statistics

The LDB is an establishment-level dataset. It is therefore necessary to merge the establishments to the firm-level since credit constraints are present at the firm rather than the establishment-level. Each firm in the dataset has an employer identification number (EIN). I merge all establishments with the same EIN to construct a firm. Establishments sharing one EIN have a joint tax liability. It does not necessarily correspond to economic control as some larger corporations have multiple EIN. As I am primarily concerned with small and young firms this does not appear to be a major issue for the present research question. As firms can have establishments in different sectors/locations, I assign to each firm that sector/location in which it has the largest share of employees. Aggregating by EIN also implies that the size of firms under one operational control but that operate under multiple EIN is understated in my dataset. It further implies that firms opening new establishments under a new EIN will be classified as young mistakenly even if the underlying parent company has long existed (see a more detailed discussion in the appendix of Haltiwanger et al. (2013)).

Second, some firms outsource employee management tasks to Professional Employer Organizations (PEO) like ADP and Insperity. While there exist about 700 hundred PEO in the U.S., the market is dominated by a few very large PEO. The two largest PEO alone, ADP and Insperity, account for more than 30% of the entire PEO market. It is important to point out that firms like ADP act as PEO for some firms - i.e. firms outsource their entire human resource management to a firm like ADP - and provide payroll services to other firms without acting as PEO. As documented by Gordon and Gordon (2006) the penetration of the market is rather small for PEO and in 2006 PEO covered only about 2 million employees, that is less than 2% of aggregate employment. In a large number of states these PEO are allowed to submit the employment information to the state under their own EIN rather than their firm client's EIN.<sup>25</sup> Suppose a PEO submits the employment information for a

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<sup>25</sup>The fact that they are allowed in same states to submit firms under the PEO EIN does not necessarily imply that the PEO actually submit for all firms under their PEO EIN. Unfortunately it is impossible to determine the number and composition of firms that are aggregated under the PEO EINs.

large number of small firms under the PEO EIN. Then by aggregating the data based on EIN this will create a large firm even though it should be in fact a large number of separate smaller firms. In order to avoid a potential bias in my estimation I use the following steps: I exclude the NAICS sector that contains the PEO. Furthermore, I exclude all EIN which reports at least one establishment in the PEO NAICS over the sample period. As some states do not require the report of all separate establishments this ensures that I remove all potential PEO that might bias the results. While this likely excludes more firms than necessary it will entirely remove all data related to PEOs.<sup>26</sup> This procedure removes only a very small percentage of the observations in the data, the information not available to the researcher is potentially more significant: The sample now excludes all the firms whose data were submitted under PEO EINs. In order to generalize the estimation results for the entire economy the underlying assumption is that firm using PEOs are on average not different from firms that are not using PEOs.

I further remove all firms in real estate and financial sectors (SIC codes 6011-6799). I also remove public administration (SIC codes 9111-9721).

Table 9: **Summary Statistics**

	<i>N</i>	Mean	Std	Median	10 Pct	90 Pct
Employment	4042853	21.43	635.86	3.67	1.00	24.33
Growth Rate	4042853	-0.19	1.14	0.00	-2.00	2.00
Employment Small	3845135	6.53	8.39	3.00	1.00	17.66
Employment Medium	179953	125.58	83	91.18	89.33	54.66
Employment Large	17765	2191.12	9330.29	950.00	554.33	3959.00
Empl. Exiters	764508	8.12	115.22	2.00	1.00	11.33
Empl. Entrants	456858	6.75	68.75	2.00	1.00	10.66

*Notes:* Growth Rate calculation is based on the symmetric growth rates as discussed above with  $\alpha = 0.5$  for 2007:Q4 to 2009:Q3. Employment Small refers to employment in firms with less than 50 employees, Employment Medium to firms with employment with more than 50 but less than 500 employees. Employment Large refers to firms with more than 500 employees

Table 9 provides summary statistics for the dataset. The average employment size is about 21 employees. This number is quite similar to the Business Dynamics Statistics (BDS) data and indicates that the lack of a corporate identifier has only a small impact. The average employment growth rate between 2007:Q4 and 2009:Q3 is -19%. We can also see that over the sample period about 450.000 firms entered while about 760.000 firms exited. The

<sup>26</sup>To further ensure that the above procedure works I separately ensure that the two largest PEO that account for about 30% of the entire PEO market - ADP and Insperty - are removed by use of their EIN which I obtained from the financial data.

statistics for entrants are computed based on their initial firm size.

### C.1.1 Other Data Sources

This paper uses additional control variables in some of the regressions that require additional data. House price data are available at the quarterly frequency from the Federal Housing Finance Agency (FHFA) for many metropolitan statistical areas (MSA, CBSA).

Employment share of construction, county level employment and income are obtained from the Bureau of Economic Analysis (BEA).

## C.2 Empirical Results: Additional Robustness Checks

This section provides several robustness checks. First, I compare the difference-in-differences estimator for the financial crisis with one for the dot-com bust of 2001. The dot-com bust was not a financial driven recession and one would thus expect that the difference-in-differences estimator is different from the findings for the 2007-2009 recession if the estimator indeed captures the effect of financial constraints. Second, I include house prices in the regression and show that the main result is robust to controlling for including house prices. Third, I provide a set of results for a sample that removes the construction sector. The financial crisis originated in the housing sector which in particular affected the construction sector. Since the construction sector belongs to the high external finance dependent sectors, the estimation results could be sensitive to removing the construction sector.

### C.2.1 Dot-com bust vs financial crisis

This section compares the difference-in-differences estimator for the financial crisis with the corresponding estimator for the 2001 dot-com-bust period. Since the dot-com bust was not financially driven one would expect the difference-in-difference estimator to be more similar to the 2004-2006 period rather than the financial crisis.<sup>27</sup> The main finding is that the difference-in-differences estimator for the 2001-2002 period is qualitatively similar to the findings for the 2004-2006 period: the sign is positive and the magnitude is similar if one takes into account that the time period is shorter. However, the differences-in-differences estimator for 2001 the finding is insignificant.

$$2001 : (\beta_{\text{small}}^{\text{high}} - \beta_{\text{large}}^{\text{high}}) - (\beta_{\text{small}}^{\text{low}} - \beta_{\text{large}}^{\text{low}}) = 0.018 \quad (\text{A-31})$$

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<sup>27</sup>Since the 2001:1 to 2002:1 period is short than the corresponding period in 2004 to 2006 it should be expected that the estimated growth rate differential is somewhat smaller.

Table 10: Effect of High external financial dependence during **2001** vs **2007-2009**

	Empl Growth 2001:1 to 2002:1 (1)	Empl Growth 2007:4 to 2009:3 (2)
small	0.069***	0.043***
large	0.023***	-0.017**
small* high	-0.019**	-0.031***
large* high	-0.037***	0.017*
2-digit SIC, State FE	yes	yes
Observations	3508760	4042853

Notes: The dependent variable is the firm-level growth rate between 2001:Q1 and 2002:Q1 in column (1) and 2007:Q4 and 2009:Q3 in column (2). Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.

This again confirms that the effect of external financial dependence has a very pronounced effect on employment growth in small firms relative to large firms. Moreover, I do not find the same effect in the period leading up to the recession nor do I find the same effect during the 2001 recession.

### C.2.2 Controlling for House Prices & Additional Controls

Mian and Sufi (2011) document that a significant fraction of the rise in U.S. household leverage between 2002 and 2006 as well 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 above I therefore add the increase in the house price index (hpi) on the MSA level between 2002-2006. Using contemporaneous house price growth instead would raise the concern that employment declines during the crisis might actually be driving a decline in home prices. The reason for adding pre-financial crisis house price growth is to avoid this potential endogeneity issues. Based on the findings by the authors discussed above we should therefore expect that based on the aggregate demand channel that employment losses were particularly strong in areas with large house price increases prior to the crisis. I further control for the the level of population, income, the share of construction in total employment, the growth rate of the population 2002-2006, the growth rate of income 2002-2006. The regression results for adding pre-recession house price growth and other controls are displayed in Table 11.

The table omits the estimation coefficient for other controls in order to focus on house price growth prior to the recession. The coefficient on house price growth is negative as one would expect: Businesses in areas of large house price growth leading up to the recessions

Table 11: **Effect of High external financial dependence during 2007-2009: House Prices**

	Employment Growth 2007:4 to 2009:3		
	(1)	(2)	(3)
small	0.036*** (0.007)		-0.092*** (0.005)
young		0.282*** (0.007)	0.030*** (0.012)
small high EFD	-0.026*** (0.008)		-0.008 (0.006)
young high EFD		-0.048*** (0.011)	0.005 (0.016)
young small			0.262*** (0.012)
young small high EFD			-0.053*** (0.017)
growth rate hpi	-0.079*** (0.016)	-0.079*** (0.017)	-0.079*** (0.017)
additional controls	yes	yes	yes
2-digit SIC, State FE	yes	yes	yes
Observations	1931795	1931795	1931795

*Notes:* The dependent variable is the firm-level growth rate between 2007:Q4 and 2009:Q3. Additional controls include the level of population, income, the share of construction in employment, the sector trade share, the growth rate of population and income between 2002-2006. Standard errors are in parentheses. Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.

were subject to a larger demand shock: households in these areas increased their leverage leading up to the crisis and in response to falling house prices cut back on consumption. Consequently these businesses reduced employment significantly. This paper on the other hand focussed on the importance of financial constraints for employment growth. This table confirms that both the aggregate demand channel and the credit channel are important determinants of employment growth during the financial crisis. As an robustness check I

Table 12: **Effect of High external financial dependence during 2007-2009: House Prices**

	Employment Growth (1)
small	0.034*** (0.007)
large	-0.024*** (0.010)
small high EFD	-0.023*** (0.008)
large high EFD	0.024* (0.014)
growth rate hpi	-0.056*** (0.013)
growth rate hpi high EFD	-0.016 (0.022)
2-digit SIC, State FE	yes
Observations	2011973

*Notes:* The dependent variable is the firm-level growth rate between 2007:Q4 and 2009:Q3. Growth rate hpi refers to the growth rate of the MSA level house price index between 2002 and 2006. Standard errors are in parentheses. Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.

recompute the difference-in-differences estimator described in section 3.3.1 but include the pre-recession house price growth and the interaction between house price growth and high EFD. Table 12 shows the results. While the growth rate of HPI has a negative sign as in the previous table, the interaction with high external financial dependence is insignificant.<sup>28</sup> The difference-in-differences estimator computed from this regression is then essentially unchanged.

$$(\hat{\beta}^{small,high} - \hat{\beta}^{large,high}) - (\hat{\beta}^{small,low} - \hat{\beta}^{large,low}) = -0.047*** \quad (\text{A-32})$$

<sup>28</sup>And remains insignificant if adding further interactions with size.

### C.2.3 Sample Without Construction Sector

Since construction was one the most affected sectors that also happens to be in the high external financial dependence category, one might be concerned that the construction sector might be driving the estimation results. This section removes the construction sector. It is otherwise identical to the previous regressions. Table (13) displays the results.

Table 13: **Effect of High external financial dependence during 2007-2009: no construction**

	Employment Growth 2007:4 to 2009:3		
	(1)	(2)	(3)
small	0.045*** (0.007)		-0.084*** (0.006)
young		0.294*** (0.008)	0.030*** (0.009)
small high EFD	-0.027*** (0.010)		-0.011 (0.008)
young high EFD		-0.036*** (0.013)	0.018 (0.014)
young small			0.274*** (0.011)
young small high EFD			-0.053*** (0.017)
2-digit SIC, State FE	yes	yes	yes
Observations	3497889	3497889	3497889

*Notes:* The dependent variable is the firm-level growth rate between 2007:Q4 and 2009:Q3. Standard errors are in parentheses. Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate the significance at the 10 percent, 5 percent and 1 percent levels.

The estimation results for the sample without construction sector generally confirm the earlier findings. All interactions with high external financial dependence are mitigated to some degree but the significance levels are essentially unchanged. Overall, the construction sector is an important factor in the estimation results for high external finance dependent firms but the results are robust if we remove construction from the sample. However, the magnitude of the effect is slightly lower.

### C.2.4 Continuing Firms only

Table 14 confirms that the results are quite different from the whole sample estimates: The effect of high external financial dependence on employment growth rates is much smaller in absolute value across columns (1)-(3) relative to the findings in the entire sample. Comparing Table 14 with Table 2 leads to the following conclusions: Column (1) in both tables shows

that for the sample of continuing firms employment growth in high EFD sectors was 1.5 percentage points lower than in low EFD sectors. The same column in the whole sample implies a reduced growth of 3.3 percentage points, more than double the effect in the sample of continuing firms. If we instead consider column (2), we see that young continuing firms in the sector of high EFD on average exhibited a 2.1 percentage point lower employment growth while the same number in Table 2 is about three times larger.

Table 14: **Effect of High external financial dependence during 2007-2009: Continuing Firms only**

	Employment Growth 2007:4 to 2009:3		
	(1)	(2)	(3)
small	0.087*** (0.005)		0.060*** (0.005)
young		0.074*** (0.017)	-0.017*** (0.006)
small high EFD	-0.015** (0.007)		-0.009*** (0.007)
young high EFD		-0.018*** (0.003)	0.008 (0.008)
young small			0.092*** (0.006)
young small high EFD			-0.027*** (0.008)
2-digit SIC, State FE	yes	yes	yes
Observations	2821487	2821487	2821487

*Notes:* The dependent variable is the firm-level growth rate between 2007:Q4 and 2009:Q3. Standard errors are in parentheses. Standard errors are clustered by state-industry. \*, \*\*, and \*\*\* indicate significance at the 10 percent, 5 percent and 1 percent levels, respectively.