ECONOMIC RESEARCH
FEDERAL RESERVE BANK OF ST. LOUIS

WORKING PAPER SERIES

Firm Exit and Liquidity: Evidence from the Great Recession

Authors	Fernando Leibovici, and David Wiczer
Working Paper Number	2023-011A
Creation Date	May 2023
Citable Link	https://doi.org/10.20955/wp.2023.011
Suggested Citation	Leibovici, F., Wiczer, D., 2023; Firm Exit and Liquidity: Evidence from the Great Recession, Federal Reserve Bank of St. Louis Working Paper 2023-011. URL https://doi.org/10.20955/wp.2023.011

Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis, MO 63166

Firm Exit and Liquidity: Evidence from the Great Recession*

Fernando Leibovici
Federal Reserve Bank of St. Louis

David Wiczer
Federal Reserve Bank of Atlanta & IZA

May 2023

Abstract
This paper studies the role of credit constraints in accounting for the dynamics of firm exit during the Great Recession. We present novel firm-level evidence on the role of credit constraints on exit behavior during the Great Recession. Firms in financial distress, with tighter access to credit, are more likely to default than firms with more access to credit. This difference widened substantially in the Great Recession while, in contrast, default rates did not vary much by size, age, or productivity. We identify conditions under which standard models of firms subject to financial frictions can be consistent with these facts.

*Contact information: fleibovici@gmail.com, wiczerd@gmail.com. We thank Matthew Famiglietti for excellent research assistance. The views expressed in this paper are those of the individual authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis, the Federal Reserve Bank of Atlanta, the Federal Reserve System, or the Board of Governors.

1 Introduction

The entry and exit of firms is a key channel in the process of creative destruction underlying the functioning of modern economies. When unproductive firms shut down during crises, they free up resources that can be later used by expanding productive firms, resulting in aggregate growth. Yet, firm entry and exit may also amplify crises in the presence of financial market frictions if productive firms with limited cash flows are forced to shut down during times of distress.

In this paper, we investigate the extent to which firm exit may be driven by the amount of liquidity available to firms. To do so, we study the dynamics of firm exit during the Great Recession of 2008/2009 in the U.S., an episode that featured an aggregate drought of liquidity along with a deep recession and a sharp increase in firm exit (Figure 1). We ask: To what extent was the increase of firm exit during the Great Recession accounted for by liquidity issues, as opposed to reflecting the natural process through which insolvent firms exit during crises?

We answer this question using a rich firm-level dataset on the universe of U.S. non-financial firms for 2000-2013, with detailed information on firms' active/inactive status, financial position, sales, and employment. We use these data to document salient features of the role of liquidity factors in accounting for firm exit during the Great Recession and to investigate their aggregate implications. We interpret our empirical findings through the lens of a model in which heterogeneous firms endogenously choose whether to exit or remain active as a function of both productivity and the degree of liquidity available. We identify three conditions under which the model is consistent with our empirical findings.

Our main findings point to the critical importance of liquidity factors in determining firm exit during the Great Recession. Specifically, we estimate firm-level financial position indicators to be much more important determinants of firm exit than firm-level fundamentals such as productivity, size, or age. In the aggregate, we find that firms in financial distress

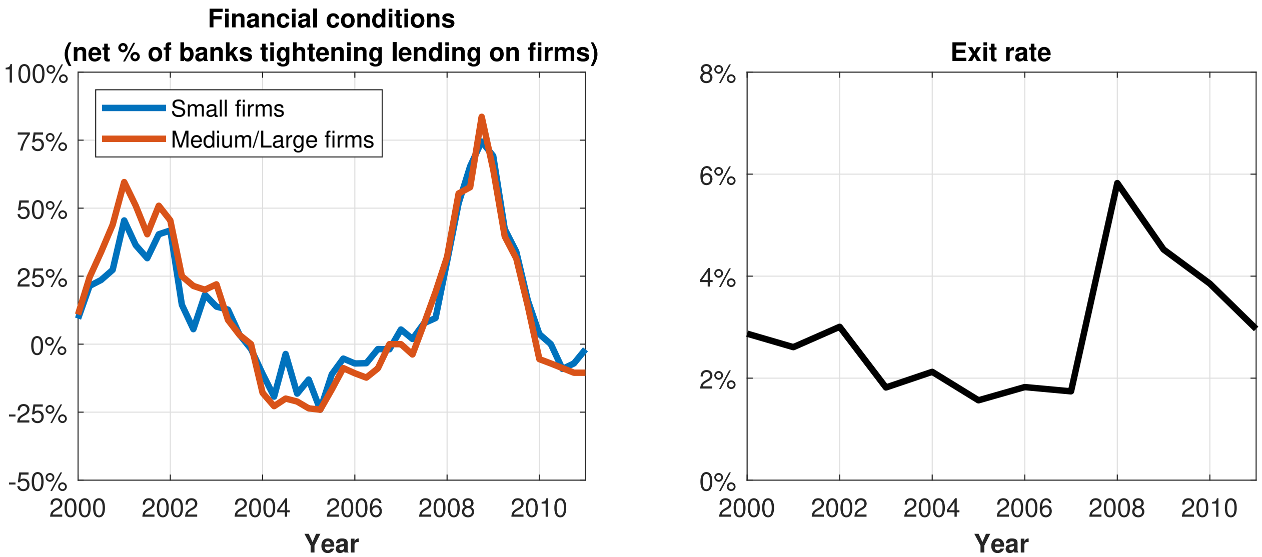

Figure 1: Great Recession, Financial Tightening, and Firm Exit

account for 30% of aggregate exit during this episode. These findings point to the potential importance of policies designed to mitigate liquidity issues during crises, as recently implemented in the U.S. during COVID-19.

We begin the paper by investigating the empirical relation between firm-level financial position and exit rates. We measure firms' liquidity position based on novel firm-level data on the degree to which firms pay their vendors on time. We identify firms as operating under financial distress if they pay their vendors late. First, we document a systematic relationship between firm exit rates and financial distress: Firms that pay their vendors late have much higher exit rates. Second, we find that differences in firm exit rates by financial distress increased substantially during the crisis. Finally, we show that these differences in firm exit rates by financial distress played an important role in accounting for the increase of the aggregate exit rate during this episode.

While these features of the data suggest that there is tight link between financial factors and firm exit, they could be jointly driven by a common alternative channel. For instance, unproductive firms or ones that produce goods that are unpopular or out of fashion might struggle to pay their vendors while also featuring high rates of exit. In such case, financial distress might proxy the low productivity of the firm rather than the tightness of credit constraints; that is, capture insolvency rather than the lack of short-term liquidity. To disentangle the role of financial factors in accounting for firm exit from fundamentals such as productivity, we set up an empirical specification with firm exit as a function of both financial factors and these alternative channels. Our main finding is that liquidity factors are a critical determinant of firm exit during the Great Recession relative to alternative factors such as firm-level productivity, size, or age.

We interpret these empirical findings through the lens of a standard model of firms with endogenous exit decisions. We consider an economy populated by a continuum of firms heterogeneous in productivity and access to liquidity. To operate, firms have to pay a fixed operation cost, which allows them to produce a homogeneous good with a decreasing returns-to-scale technology. Firms are subject to a financial constraint that requires them to pay a fraction of their costs before revenues accrue. These upfront payments are financed through internal funds, as well as through loans obtained as a function of firms' net worth.

We use this setup to study the determinants of firms' exit decisions. We ask: To what extent are firms' decisions to operate determined by productivity or access to liquidity? Generically, the model implies that firms' operation decisions are jointly determined by both productivity and the amount of liquidity available. In the model, conditional on a given level of productivity, higher liquidity increases firms' operation scale and the likelihood that they will find it profitable to operate. Similarly, conditional on a given level of liquidity, higher productivity increases the scale of firms' operations, increasing profitability and the likelihood that they choose to operate.

The generic implication that both productivity and liquidity jointly determine exit is a stark contrast to our empirical findings. Thus, we ask: What conditions can reconcile the model's implications for the determinants of firms' operation decisions with our empirical findings? Three conditions allow the model to make exit be determined by liquidity factors but not by productivity: (i) firms do not need to pay their variable production costs upfront, (*ii*) firms' fixed operation costs are proportional to productivity, and (*iii*) firms' access to finance is increasing in productivity. Condition (*i*) implies that firms operate at their unconstrained production scale. Condition (*ii*) implies that firms' profits are not increasing in productivity: As firms' scale and variable profits increase, so do the fixed costs, offsetting these gains, akin to a zero-profit condition but applying to the exit decision. Condition (*iii*) implies that firm productivity alleviates financial constraints, consistent with many micro-founded motivations for such frictions. The combined impact of these assumptions is that firms' operation decisions are no longer determined by firms' productivity. But in contrast, they continue to be determined by liquidity, which is critical for financing the fixed operation cost.

These findings point to the importance of liquidity to finance operational costs. Conditions (*i*) and (*ii*) point to the importance of costs that scale with size and productivity but which cannot be adjusted faster than debts are due, such as long-term supplier contracts or rent and utilities. While there are many approaches to modeling financial constraints, our conditions are consistent with previous studies, e.g. Midrigan and Xu (2014), and supported by, e.g. Bergin, Feng, and Lin (2021). The third condition is in line with much of the literature that micro-founds financial constraints with models of imperfectly enforced contracts, which typically imply that productive firms have better access to finance (Albuquerque and Hopenhayn 2004; Clementi and Hopenhayn 2006). Taken together, our model implies that the Great Recession's shock to liquidity reduced firms' ability to finance their fixed operation costs, leading financially vulnerable firms to shut down.

This paper contributes to a large literature that investigates the Great Recession to learn about the role of financial factors on firm-level decisions. Closely related to our work are Khan, Senga, and Thomas (2014) and Arellano, Bai, and Kehoe (2016), who study the role of firm-level default on the dynamics of U.S. aggregate dynamics during the Great Recession. We contribute to this literature by using a novel dataset with information on firms' financial distress to study the role of credit market frictions on the dynamics of firm exit during crises. Our paper is also closely related to Dinlersoz, Kalemli-Ozcan, Hyatt, and Penciakova (2018) Ebsim, Faria-e Castro, and Kozlowski (2023), and Gourinchas, Kalemli-Özcan, Penciakova, and Sander (2021), who study the role of credit market frictions in the response of U.S. firms during large crises, such as the Great Recession or COVID-19. Our empirical observations are also consistent with models of cyclical credit tightening, such as Farboodi and Kondor (2021) or Gorton and Ordoñez (2014), where financially vulnerable borrowers are most affected.

Our paper is more broadly related to a literature that investigates the role of financial factors during the Great Recession, with a focus on households, firms, and financial institutions. For instance, see Chodorow-Reich (2013) or Mian and Sufi (2009) for examples of studies focused on households, and Chodorow-Reich and Falato (2017) or Gertler, Kiyotaki, and Queralto (2012) for examples of studies focused on the financial sector. For a more thorough review of this literature, see Gertler and Gilchrist (2017) and Mian and Sufi (2018).

The rest of the paper is structured as follows. In Section 2, we conduct the empirical analysis. In Section 3 we set up the model and study its implications. Section 4 concludes.

2 Access to finance and firm exit during the Great Recession

In this section we investigate the role of access to finance on the dynamics of firm exit during the Great Recession. To do so, we exploit a novel dataset with the near-universe of U.S. establishments around this period. We begin our analysis by describing the data and the key variables that we study. We then investigate the relation between firm exit and their financial position. First, we examine the unconditional relationship between firms' financial conditions and exit and then control for other potentially key mechanisms that could account for the patterns that we document. We conclude this section by examining the aggregate implications of our findings.

2.1 Data

Our firm-level dataset is the National Establishment Time-Series (NETS) database collected by Dun and Bradstreet (D&B), which contains annual longitudinal information on the universe of establishments in the United States over recent decades. Among other variables, the dataset provides information on establishments' credit ratings and whether they are active, allowing us to identify when firms exit. In addition, it contains information on a range of other dimensions, such as establishment-level sales, employment, and age.

Given our focus on exit, financial constraints and aggregate financial conditions, we conduct our analysis at the firm level rather than at the establishment level because financial constraints likely bind at the firm level if resources can be shared across establishments. The basic unit of observation in the NETS is an establishment, so we aggregate within firms by exploiting information on the headquarters of the firm to which each establishment belongs. In particular, for each establishment i, the dataset provides information on the establishment code j of the headquarters of the firm to which it belongs.[1] Then, we aggregate the dataset to the firm-level by identifying all establishments with a common headquarters as being part of the same firm. We aggregate all quantitative variables across establishments of a common firm by weighting their respective values by the number of workers employed in each establishment and year.[2]

Throughout the paper we restrict attention to the period 2000-2013 and focus on firms with at least 10 employees on average over the sample for comparability with other datasets and to avoid firms that are often non-employers, such as individual workers who take 1099 income or households with occasional domestic services.

Credit ratings, delinquency, and financial distress The credit ratings in the dataset are Paydex scores, which characterize the timeliness of an establishment's payments to sup-

[1] Note that $i = j$ for single-establishment firms.

[2] Note, however, that all the findings reported in the paper are robust to examining the data at the establishment-level.

pliers. In particular, D&B collects payment histories from the establishment's vendors and assigns a Paydex score to reflect the reported timeliness. This score is used by banks, vendors, and other institutions to assess the ability of establishments to fulfill their obligations.

The Paydex score of an establishment is a value between 0 and 100. A score equal to 80 is assigned to establishments that pay vendors and suppliers on time. More generally, a score equal to 100 is assigned to establishments that pay their vendors at least 30 days ahead of time, a score equal to 50 is assigned to establishments that are 30 days late with payment, and a score between 1 and 19 reflects payments over 120 days past due. For an establishment to be assigned a Paydex score, D&B requires it to have information on at least 4 payments.

According to D&B, firms with Paydex scores between 80 and 100 have "low risk of late payment," firms with Paydex score between 50 and 79 have "moderate risk of late payment," and firms with Paydex score between 0 and 49 have "high risk of late payment."[3] We abstract from this particular mapping between Paydex scores and firm-level riskiness; instead, we focus directly on the information on late vs. early payment encoded in the different values taken by Paydex scores.

The NETS database reports each establishment's minimum and maximum Paydex scores each year. We measure each establishment's credit rating as captured by their minimum Paydex score. Thus, we consider an establishment to have a low credit rating if it had a low credit rating at any point in a given year. To analyze Paydex scores at the firm-level, we aggregate establishments that share a common headquarters and weight the minimum Paydex scores by the number of employees across the different establishments.

We partition firms into two groups based on their financial position. We identify firms as in financial distress in a given year if they were delinquent at least 30 days late once that year—that is, if their minimium Paydex score is 50 or lower. The remaining firms with a valid Paydex score are classified as in good financial standing. Our findings are robust to

[3]For more information, see `http://www.dandb.com/glossary/paydex`.

	Good financial standing	Financial distress
Avg. # of firms	981,693	112,392
Avg. sales	$13,507,761	$4,301,553
Avg. # of workers	103.2	39.4
Avg. sales per worker	$139,208	$124,560
Avg. age	33.5	24.9

Table 1: Summary statistics by financial standing, Avg. 2006-2012

alternative classifications of firms by financial standing.

Summary statistics We begin our analysis by contrasting summary statistics between firms in good financial standing and firms in financial distress.

Table 1 reports, for each of these types of firms, the average value for 2006-2012 of the different variables examined. The vast majority of the firms in the dataset are in good financial standing (89.7% of all firms). These firms are larger in both sales and number of workers, more productive, and older than their counterparts in financial distress. For instance, firms in good financial standing have average sales and number of workers that are 3.14 and 2.62 times, respectively, than their financially distressed counterparts.

Yet, a firm's financial standing is not a fixed characteristic; rather, it is a state that firms may transition through. To examine firms' typical transition dynamics between good financial standing, financial distress, and exit, Table 2 reports the average transition probability matrix across these states for the period 2006-2012. The values reported in the table are interpreted as follows: Given a firm's financial standing in period t (as given by the rows of the table), what is the probability that they transition to the various states in period $t+1$ (as given by the columns of the table)?

Good financial standing is a very persistent state. Conditional on being in good financial standing in period t, in the following period 93.8% of the firms remain in good standing, 3.6% transition to being in financial distress, and 2.9% of firms exit. In contrast, conditional

$t \setminus t+1$	Good standing	Financial distress	Exit
Good standing	0.938	0.036	0.029
Financial distress	0.261	0.655	0.069

Table 2: Transition probabilities: Good financial standing, financial distress, exit

on being in financial distress in period t, we find that in the following period 65.5% of the firms remain in financial distress, 26.1% transition to being in good financial standing, and 6.9% of firms exit.

Firms in financial distress are more than twice as likely to exit than firms in good financial standing. While this evidence suggests financial distress may causally lead firms to be more likely to exit, Table 1 shows these firms are different along a number of other dimensions that could also play a role in accounting for the differential exit probabilities. We study the differential impact of the various channels in the following sections.

Establishment exit: NETS vs. QCEW vs. BDS Before we begin to study the link between financial distress and firm-level exit using this data, we first examine whether the information on exit in this data is consistent with other publicly available data sources.[4] To do so, we focus on (*i*) the Quarterly Census of Employment and Wages (QCEW) produced by the U.S. Bureau of Labor Statistics (BLS), with data on active establishments accounting for more than 95% of jobs in the U.S., and on (*ii*) the Business Dynamics Statistics (BDS) produced by the U.S. Census Bureau. To maximize the comparability between our data and these sources, we focus on establishment exit rates rather than firm-level exit rates as we do in the rest of the paper.

Given our focus on the Great Recession, we begin by focusing on the growth rate in the number of establishments between 2008 and 2009—Table 3 reports this value for QCEW, BDS, and establishments in the NETS dataset. We find the information on establishment-

[4]Crane and Decker (2019) notably compare aggregate dynamics in NETS to other data sources. They show that, under certain restrictions that we follow in our analysis, NETS can be made to mimic official employer datasets with reasonable precision.

Number of establishments	% change 08-09
Business Dynamics Statistics (U.S. Census)	−2.0%
Quarterly Census of Employment and Wages (BLS)	−4.1%
NETS establishments	−5.1%

Table 3: Establishment dynamics: NETS vs. QCEW (BLS)

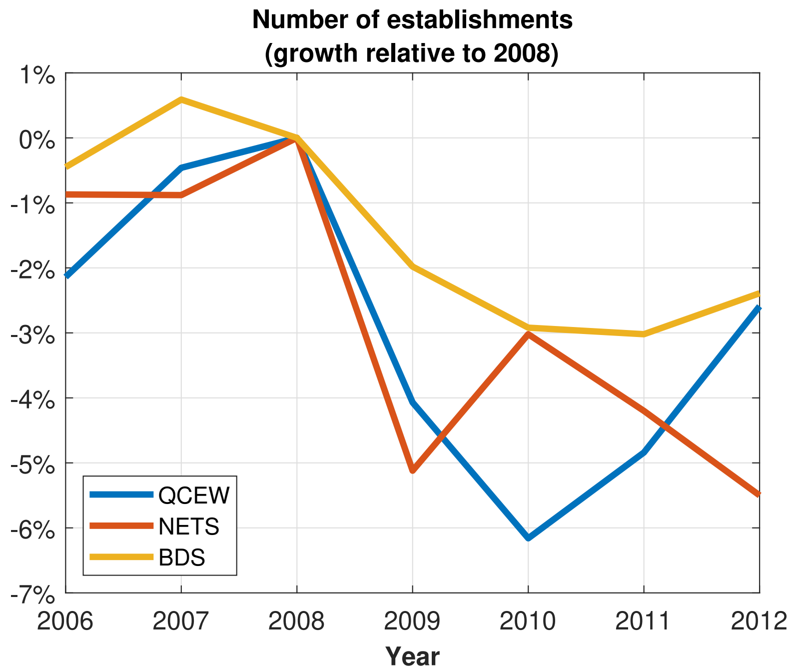

Figure 2: Establishment growth relative to 2008: NETS vs. QCEW vs. BDS

level exit in NETS is largely consistent with the rate of exit documented in QCEW and BDS: The number of establishments declined by −5.1% in NETS, whereas they declined by −4.1% in QCEW and by −2.0% in BDS.

Figure 2 compares the growth in the number of establishments relative to 2008 over a longer time span. The NETS-based establishment dynamics typically fall in between the dynamics implied by QCEW and BDS. These findings show that the data on exits available in the NETS dataset is consistent with standard official sources produced by the BLS and the U.S. Census Bureau.

2.2 Financial factors and firm exit

We begin by examining the relation between financial factors and firm-level exit rates. To do so, we focus on Paydex scores, which, as described above, can be interpreted to measure firms' financial position.

The left panel of Figure 3 contrasts the dynamics of firm-level exit rates between firms in good financial standing relative to firms in financial distress, which were delinquent for at least 30 days at least once in the year. For context, we also plot the dynamics of the aggregate exit rate. We observe that firm-level exit rates depend systematically on firms' financial position. In particular, in every year of the sample, firms in good standing have systematically lower exit rates than firms that pay late. This relationship is, moreover, quantitatively significant: For instance, the exit rate of financially distressed firms is at least 2 percentage points higher through most of the sample.

The right panel of Figure 3 disaggregates firm-level exit rates across a finer set of financial position categories, as captured by Paydex scores. As in the left panel, we observe that firms' exit rates depend systematically on their financial position, monotonically decreasing as their financial improves. That is, firms with better Paydex scores systematically exhibit lower exit rates.

The figure also shows that the exit rate of firms with subpar payment performance (which pay at least 30 days late) increases substantially during the Great Recession. For instance, firms that were 60 to 90 days late at some point in the year exited at a 5% rate in the years prior to the crisis, while they exited at a nearly 20% rate between 2008 and 2009. In contrast, the exit rates of firms in better financial standing featured a much milder increase — by less than 5 percentage points for firms less than a month late.

The substantial increase of exit rates among firms with weak financial position also affected the dynamics of firm-level exit in the aggregate. On the one hand, we observe that the aggregate exit rate and the exit rate of firms in good financial standing have moved together for most of the sample up to 2008. In contrast, we observe that this strong link

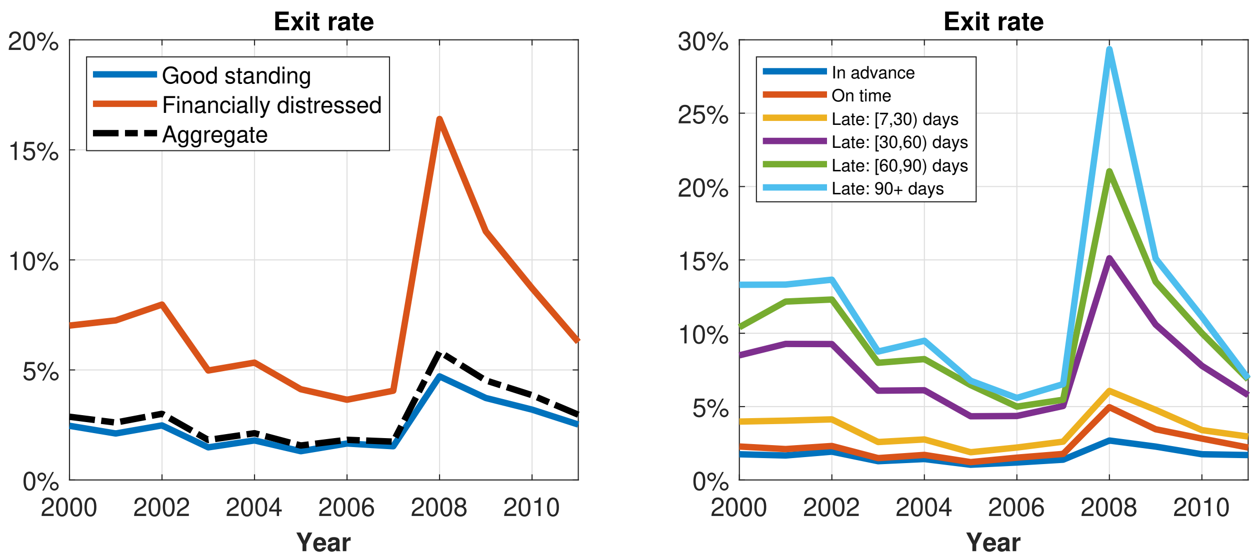

Figure 3: Firm-level financial position and exit rates

between the two exit rates breaks down in 2008 and subsequent years. Our interpretation of this gap between the aggregate exit rate and the exit of firms with good financial standing is that it is accounted for by the substantial increase of exit rates among firms in financial distress.

These findings suggest that financial factors play a key role in accounting for firms' exit decisions during both normal and crises times. Moreover, they suggest that firms' financial standing may play a particularly fundamental role in accounting for firm-level exit patterns during shocks such as the recent financial crisis.

2.3 Firm exit: Financial vs. other factors

We now contrast these findings with the relationship between firm-level exit rates and other characteristics observed in our dataset. Though the data are quite rich, we focus on characteristics that previous studies suggested played an important role in accounting for firm-level exit rates. In particular, we examine the role of firm size, productivity, and age in accounting for cross-sectional differences in firm-level exit rates. We measure firm size by number of workers and sales, and proxy productivity as sales per worker.

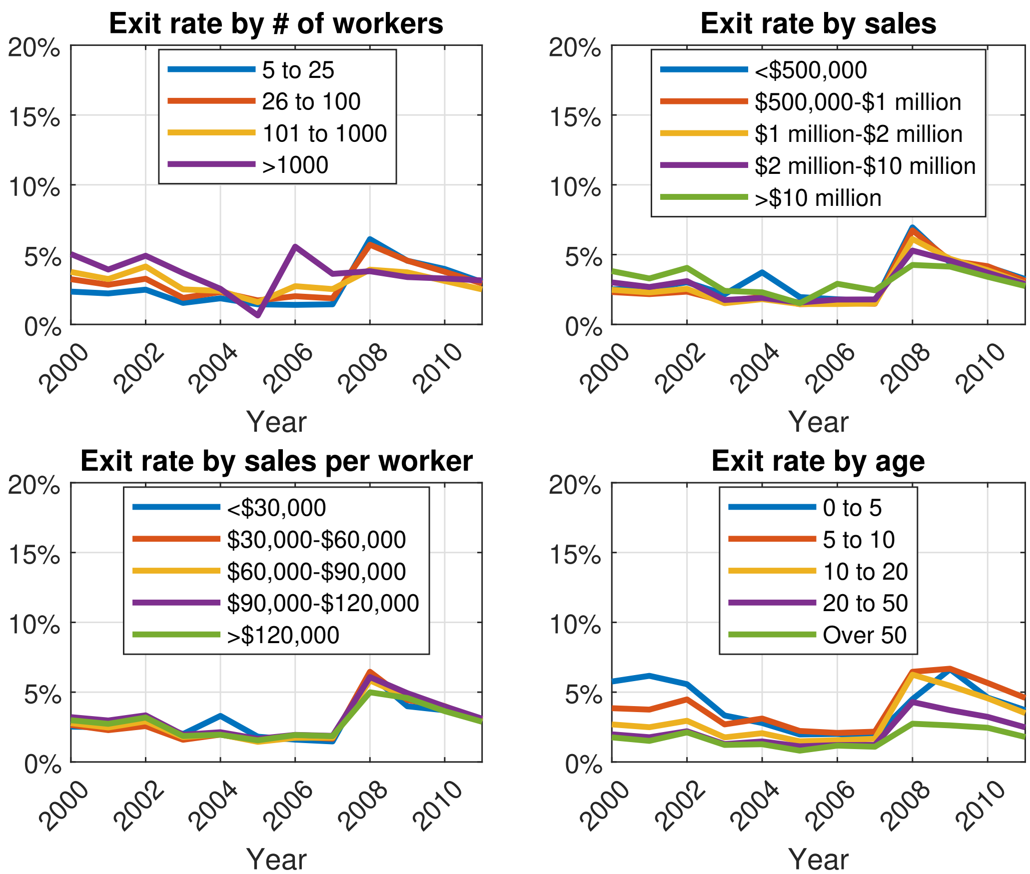

Figure 4: Firm-level exit and non-financial factors

Unconditional Figure 4 plots the exit rates conditional on (*i*) number of workers, (*ii*) sales, (*iii*) sales per worker, and (*iv*) age. We refer to these exit rates as "unconditional" as we examine these channels one at a time, without controlling for other variables. The most striking outcome we observe is that differences along any of these other dimensions generate much smaller differences in exit rates than those reported in Figure 3 based on Paydex scores. While previous studies have shown these dimensions to be important determinants of firm-level decisions, our findings suggest that differences along these dimensions are not likely to be important to the dynamics and cross-sectional differences in exit rates.

Regression analysis We now investigate whether the differences in firm-level exit by financial position documented in Figure 3 are robust when controlling for the observables examined in Figure 4. To do so, we consider a specification for whether firm i exits in a given period t as a function of both its financial position in that period, as well as a function of the other observables under analysis. In particular, we estimate the following specification:

$$\begin{aligned}\text{Exit}_{it} = &\sum_{j=2000}^{2012} \beta^j \times \text{Financially distressed}_{it} \times \text{Year}^j_{it} + \sum_{k=1}^{4} \sum_{j=2000}^{2012} \alpha^{jk} \times \text{Age}^k_{it} \times \text{Year}^j_{it} + \\ &\sum_{k=1}^{5} \sum_{j=2000}^{2012} \gamma^{jk} \times \text{Sales per worker}^k_{it} \times \text{Year}^j_{it} + \sum_{k=1}^{5} \sum_{j=2000}^{2012} \eta^{jk} \times \text{Workers}^k_{it} \times \text{Year}^j_{it} + \varepsilon_{it},\end{aligned}$$

where Exit_{it} is an indicator that is equal to 1 if the firm exists between period t and $t+1$ (that is, its last active period is t), $\text{Financially distressed}_{it}$ is an indicator that is equal to 1 if the firm is financially distressed as defined above, Age^k_{it} is an indicator that is equal to 1 if the firm belongs to age group k, $\text{Sales per worker}^k_{it}$ is an indicator that is equal to 1 if the firm's sales per worker belongs to group k, Workers^k_{it} is an indicator that is equal to 1 if the firm's number of workers belong to group k, and Year^j_{it} is an indicator that is equal to 1 if observation $j = t$. Note that firms' classification into groups based on age, sales per worker, and number of workers is as defined in Figure 4. Finally, $\{\beta^j, \alpha^{jk}, \gamma^{jk}, \eta^{jk}\}$ are coefficients to be estimated and ε is an error term with zero mean.

The key estimates that we are interested in are $\{\beta^j\}$, the coefficients on the interaction between the financially distressed and year indicators, which capture the difference in exit rates between firms that are financially distressed and ones in good financial standing — we refer to these differences as the excess exit rates.

Table 4 reports the estimation results for four alternative versions of the specification above. Column 1 reports the results from estimating the model without the interactions between year indicators and age groups, worker groups, and sales per worker groups. These estimates correspond to the unconditional estimates presented in Figure 3. Column 2 reports the results from estimating the model with controls as described above. And, finally, columns 3 and 4 report the results from re-estimating columns 1 and 2 but including county and industry fixed effects. Given that all coefficients on the interaction between years and the financially distressed indicator are statistically significant at the 1% level, we simplify the

	Dependent variable: Exit indicator			
	(1)	(2)	(3)	(4)
Financially distressed × Year				
2000	0.046	0.043	0.044	0.042
2001	0.051	0.048	0.049	0.047
2002	0.055	0.053	0.053	0.052
2003	0.035	0.034	0.034	0.033
2004	0.035	0.033	0.034	0.033
2005	0.028	0.026	0.027	0.026
2006	0.020	0.019	0.019	0.019
2007	0.025	0.023	0.023	0.022
2008	0.117	0.102	0.102	0.099
2009	0.076	0.072	0.072	0.069
2010	0.055	0.052	0.052	0.049
2011	0.038	0.035	0.036	0.034
2012	0.070	0.065	0.066	0.063
Controls				
Age groups × Year	No	Yes	No	Yes
Workers groups × Year	No	Yes	No	Yes
Sales per worker groups × Year	No	Yes	No	Yes
Fixed effects				
Counties	No	No	Yes	Yes
Industries (3-digit NAICS)	No	No	Yes	Yes
Observations	12,800,845	12,583,933	12,583,487	12,583,487
R-squared	0.016	0.018	0.023	0.025

Note: The dependent variable consists of an indicator that is equal to 1 for firm i in period t if the firm is active in period t but inactive from period $t+1$ onwards. The financially distressed indicator variables is defined as described in the paper. All coefficients on the interaction between years and the financially distressed indicator are statistically significant at the 1% level.

Table 4: Excess exit rate of delinquent firms: Regression analysis

exposition by abstracting from reporting the standard errors.[5]

Table 4 contains two key messages. First, we find that the estimated excess exit rates decline as we control for other observables and include fixed effects at the county and industry level. Second, these controls do not affect excess exit quantitatively very significantly. To illustrate the extent to which this is the case, Figure 5 plots the excess exit rates implied by the specification without any controls (column 1) and those implied by the model with controls and fixed effects (column 4).

[5]See the Online Appendix for details.

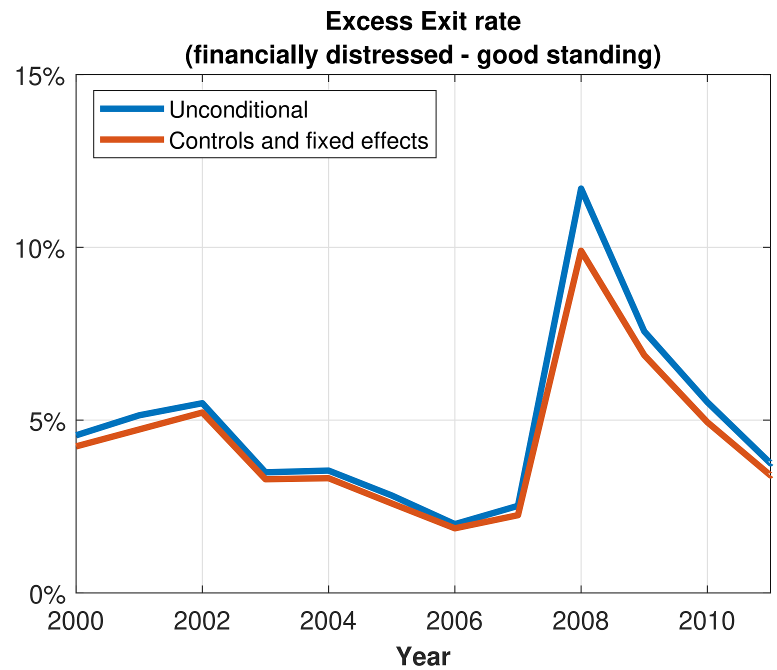

Figure 5: Excess exit rate

Our findings show that the importance of financial factors in accounting for firm exit during the Great Recession is robust to controlling for a number of other firm observables that are often modeled as determinants of firms' financial position and exit (e.g., productivity, size, age). During normal times, the likelihood that firms in financial distress exit is less than 5% higher than firms in good financial standing. During the Great Recession, we find that firms in financial distress have a 10% higher probability of exit than their counterparts in good financial standing during this episode.

2.4 Aggregate exit rate decomposition: Role of financial factors

To what extent do financially distressed firms account for the increased exit rate during this episode in the aggregate? There were quantitatively and statistically significant differences in exit rates between firms in financial distress and good financial standing during the Great Recession. But, to what extent can this relatively small set of firms drive the aggregate increase in exit?

To answer this question, we decompose the aggregate exit rate into the contribution of firms in financial distress and firms in good financial standing. We begin by defining the aggregate exit rate as:

$$\text{Exit rate}_t = \frac{\sum_{i\in\mathcal{I}} \mathbb{I}_{\{i\in N_t, i\notin N_{t+1}\}}}{\sum_{i\in\mathcal{I}} \mathbb{I}_{\{i\in N_t\}}},$$

where N_t denotes the set of firms that are active in period t, and $\mathcal{I}$ denotes the set of all firms ever active in the dataset. That is, the exit rate between period t and $t+1$ consists of dividing the number of firms active in t that are not active in $t+1$ (the numerator) by the total number of firms active in t (the denominator).

Consider now a partition of the firms into J groups (e.g., financial position, age, productivity, size). The aggregate exit rate can be linearly decomposed into an expression of the size of each group and their exit rate. This yields the contribution of each of the groups to the aggregate exit rate:

$$\text{Exit rate}_t = \sum_{j=1}^{J} \left(\underbrace{\frac{\sum_{i\in\mathcal{I}} \mathbb{I}_{\left\{i\in N_t^j\right\}}}{\sum_{i\in\mathcal{I}} \mathbb{I}_{\{i\in N_t\}}}}_{\text{Share of firms in group } j} \underbrace{\frac{\sum_{i\in\mathcal{I}} \mathbb{I}_{\left\{i\in N_t^j, i\notin N_{t+1}\right\}}}{\sum_{i\in\mathcal{I}} \mathbb{I}_{\left\{i\in N_t^j\right\}}}}_{\text{Group } j\text{'s exit rate}} \right),$$

where N_t^j denotes the set of firms that are active in period t and which belong to group j. A given group j's contribution to the aggregate exit rate is a function of the product of the share of all firms that belong to group j, and the magnitude of the group's exit rate.

Finally, the change in the aggregate exit rate between period t and $t-1$ can be linearly decomposed into the contribution of each group $j = 1, ..., J$ as follows:

$$\Delta\text{Exit rate}_t = \sum_{j=1}^{J} \Delta \left(\underbrace{\frac{\sum_{i\in\mathcal{I}} \mathbb{I}_{\left\{i\in N_t^j\right\}}}{\sum_{i\in\mathcal{I}} \mathbb{I}_{\{i\in N_t\}}}}_{\text{Share of firms in group } j} \underbrace{\frac{\sum_{i\in\mathcal{I}} \mathbb{I}_{\left\{i\in N_t^j, i\notin N_{t+1}\right\}}}{\sum_{i\in\mathcal{I}} \mathbb{I}_{\left\{i\in N_t^j\right\}}}}_{\text{Group } j\text{'s exit rate}} \right), \tag{1}$$

where Δ denotes the first difference operator, which we use here to denote the difference

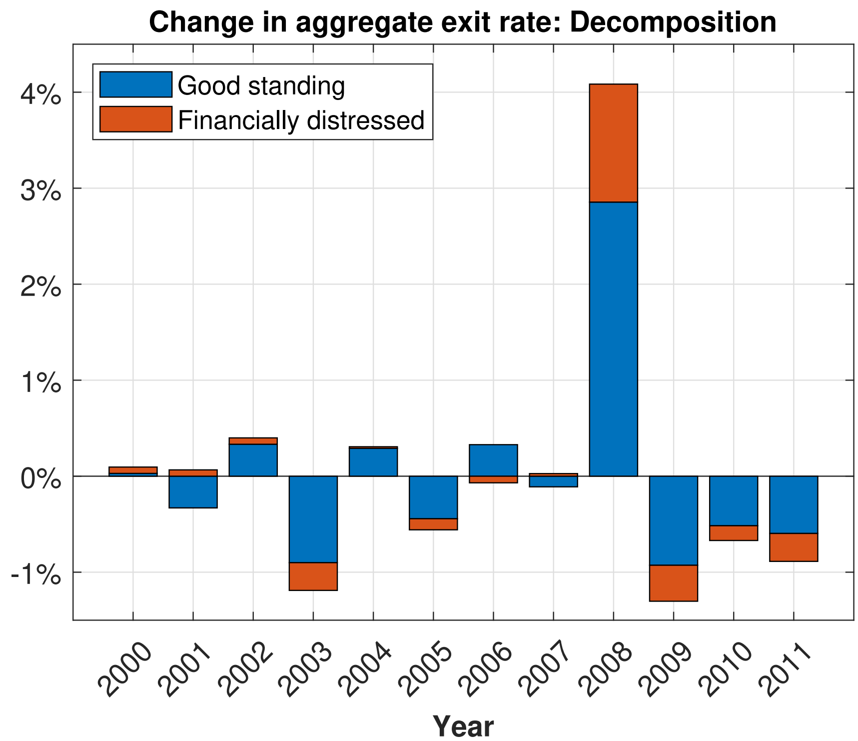

Figure 6: Aggregate exit rate decomposition

between periods t and $t-1$.

We use Equation 1 to decompose the contribution of financially distressed firms to the increase of the aggregate exit rate during the Great Recession. That is, we partition firms into two groups based on their financial position and evaluate Equation 1. Figure 6 plots our findings.

For each year, Figure 6 plots a bar showing the change in the aggregate exit rate. For instance, in 2008 the aggregate exit rate increased by approximately 4.1 percentage points. Based on Equation 1, the figure decomposes the contribution of financially distressed firms to this increase in the aggregate exit rate. We find that financially distressed firms accounted for 1.2 percentage points of the total increase, while firms in good financial standing accounted for the remaining 2.9 percentage points.

These findings show that financially distressed firms had an exceptionally large contribution to the increase of the aggregate exit rate. While financially distressed firms only accounted for 9.5% of all firms in 2008, they account for 30% of the total increase of the aggregate exit rate. Note that financially distressed firms also had an exceptionally large contribution to the subsequent decline of the aggregate exit rate in the crisis' aftermath. This was mostly due to the decline of their exit rates rather than a decline in the share of financially distressed firms.

2.5 Alternative definition of financial distress

One potential concern with our findings is that financial distress may not lead to exit but, instead, that when firms decide to exit they choose to default on their obligations. To examine the extent to which our findings may be affected by this possibility, we consider an alternative definition of financial distress: We classify firms as financially distressed in year t if they were at least one month late in their payments in year $t-3$ (that is, 3 years prior). Then, we examine whether financially distressed firms under this definition experienced similar exit dynamics as in our baseline analysis.

Figure 7 plots the exit rate dynamics by financial position using the alternative definition under consideration. Figure 3 illustrates that the implied dynamics of firm-level exit are very similar to those under our baseline definition of financial distress. This is perhaps unsurprising given the persistence of financial distress, but, importantly, it argues against reverse causality to account for our findings. There is limited scope that because firms are about to exit they begin paying late and receive low Paydex scores.

3 Theoretical analysis

In this section we set up a model to interpret our empirical findings. Our goal is to investigate the factors underlying the exit patterns observed in the data. We ask: To what extent can a standard model with heterogeneous firms subject to credit constraints account for these? We answer this question by setting up a simple model to inform us about the determinants of firms' exit decisions, and the importance of financial factors relative to other standard

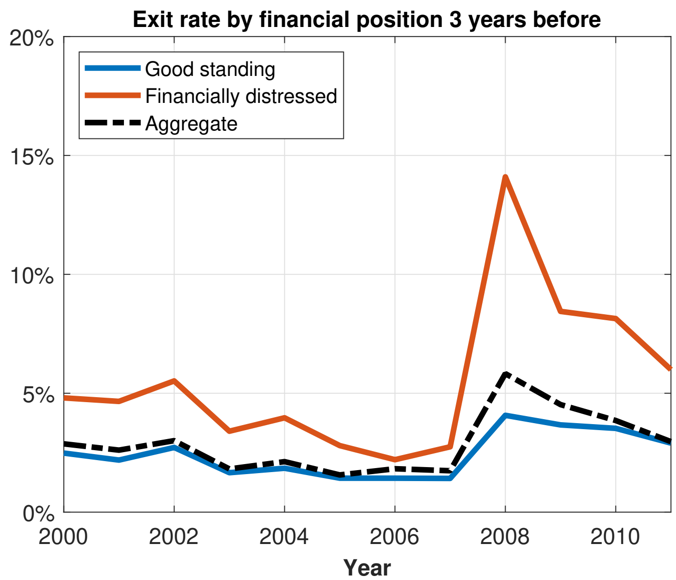

Figure 7: Firm-level financial position and exit rates: Alternative definition

ones such as productivity or size. Given that we focus on the qualitative implications of the model, we restrict attention to a static partial equilibrium environment in order to keep the analysis analytically tractable.

3.1 Setup

We consider an economy populated by a unit measure of firms heterogeneous in productivity z and net worth a. Firms are indexed by $i \in [0, 1]$, but we omit it for simplicity unless needed. Firms produce a homogeneous good that is sold at the price of the numeraire good. Production y results from hiring labor at wage rate w to operate a decreasing returns to scale technology with idiosyncratic productivity z: $y = z^{1-\alpha} n^{\alpha}$, where α controls the contribution of labor to production relative to productivity.

Firms' operations require the payment of fixed operation costs $\phi(z)F$ in units of the homogeneous good, where F controls the magnitude of the costs, and $\phi(z)$ controls the dependence of fixed costs on idiosyncratic productivity. This specification allows us to capture the extreme case where fixed operation costs are independent of the firms' idiosyncratic productivity, as well as more general cases where these depend on firms' productivity but are independent of the effective scale of operation.

Firms operate subject to a working capital requirement, whereby fixed operation costs and a fraction $\nu(z)$ of the wage bill need to be paid before revenues accrue. In the absence of credit market frictions, firms may borrow these costs in full, preventing the timing of payment from distorting firms' production decisions. To study the role of financial factors on firms' decisions, we assume that they operate subject to credit constraints, which we model as a collateral constraint following Kiyotaki and Moore (1997), Midrigan and Xu (2014), and Buera, Kaboski, and Shin (2011), among others. In particular, we assume that firms can post their net worth as collateral, which allows them to borrow $\theta(z)$ units of the good per unit of net worth. These loans are intra-temporal, and, thus, we assume their interest rate is zero for simplicity. Then, firms with net worth a operate subject to the following working capital constraint:

$$\nu(z)wn + \phi(z)F \leq \theta(z)a.$$

Notice that each term of the financial constraint is allowed to generically depend on z since they can often be state-dependent in models of financial constraints.

Firms maximize profits and the timing is as follows: Firms first choose whether to operate and then choose the amount of labor to hire for the production of the good. These choices determine the amount borrowed to pay for the working capital requirements, as well as the firms' profits. Thus, the problem of a firm with idiosyncratic productivity z and net worth a is given by:

$$g(a, z) = \max \{v(a, z), 0\},$$

where we have:

$$v(a,z) = \max_n z^{1-\alpha} n^\alpha - wn - \phi(z)F$$
$$\text{subject to}$$
$$\nu(z)wn + \phi(z)F \le \theta(z)a.$$

Given $\phi(z)F > 0$ for all z, there exist firms with productivity z and net worth a such that they cannot afford to finance the fixed operation cost: $\phi(z)F > \theta(z)a$. We assume $v(a,z) = -K$ for these firms, where $K > 0$. Thus, these firms do not choose to operate the firm.

3.2 Analytical approach

In the next subsections we investigate the role of productivity and financial factors in accounting for firm exit, and we study the extent to which the model can account for the empirical patterns documented in Section 2. In particular, we focus on two salient features of the data: (*i*) the independence of firm-level exit on productivity, and (*ii*) the importance of financial factors in accounting for firm-level exit. We investigate the extent to which our model can account for these features of the data.

Given the static nature of the model, we interpret firms' decision about whether to operate as characterizing the exit decisions of previously active firms. Then, we use the model to study the following two questions: (*i*) What is the role of productivity on firm-level exit? and (*ii*) What is the role of financial factors on firm-level exit?

More formally, this static analysis can be interpreted by considering the operating choices in two consecutive time periods, t and $t+1$. Let t be the initial time period, and let $M_t \subset [0,1]$ denote the set of firms that are active that period. Suppose, for instance, that period $t+1$ is identical to period t except that firms can borrow less per unit of collateral, a decline in θ. Then, firms in a different subset of the state space will find it optimal to operate, and the set of firms that operate in $t+1$ is M_{t+1}. Abstracting from entry, the set of firms that exit between periods t and $t+1$ consists of those that operate in period t but do not operate in period $t+1$: $M_t \setminus M_{t+1}$. Thus, studying the dependence of firms' operation choices on productivity and finance in t and $t+1$ is equivalent to studying the dependence of those that exit on these factors.

3.3 Productivity and finance jointly determine exit

We begin by investigating the determinants of firm exit. Our main finding is that exit depends jointly on both productivity z and the extent to which firms have access to finance $\theta(z)a$. These findings are encoded in the following proposition:

Proposition 1. *Firm-level exit is jointly determined by productivity z and net worth a.*

Proof. Firms choose to exit if $v(a,z) < 0$. Then, the proof of the proposition consists of showing that the firms' value function $v(a,z)$ is jointly determined by z and a. There are two cases to consider depending on whether the borrowing constraint binds or not. We consider each of these cases in turn.

Case 1: Firm is unconstrained The optimal labor choice is given by

$$n_u(z) = \left[\frac{w}{z^{1-\alpha}\alpha}\right]^{\frac{1}{\alpha-1}},$$

which implies that profits are

$$v(a,z) = zw^{\frac{\alpha}{\alpha-1}}(\alpha)^{\frac{\alpha}{1-\alpha}}(1-\alpha) - \phi(z)F.$$

Thus, we observe that productivity z generically affects the value of unconstrained firms, thereby affecting firm exit. Given that the firm is unconstrained, financial factors do not affect exit in this case.

Case 2: Firm is constrained If the constraint binds, we then have that $\nu(z)wn+\phi(z)F = \theta(z)a$. Then, the amount of labor hired by the firm is given by:

$$n_c(a,z) = \frac{\theta(z)a - \phi(z)F}{\nu(z)w},$$

and profits are then given by:

$$v(a,z) = z^{1-\alpha}\left[\frac{\theta(z)a - \phi(z)F}{\nu(z)w}\right]^{\alpha} - \left[\frac{\theta(z)a - \phi(z)F}{\nu(z)}\right] - \phi(z)F.$$

Notice that, in this case, profits are also a function of both productivity z and net worth a. Conditional on the financial constraint binding, profits are increasing in net worth a and also a function of the productivity level.

Optimal choice The optimal choice ultimately depends on whether the constraint binds. The following equation characterizes the set of threshold values of productivity z and net worth a at which the constrained choices equal the unconstrained ones:

$$\frac{\theta(z)a - \phi(z)F}{\nu(z)w} = \left[\frac{w}{z^{1-\alpha}\alpha}\right]^{\frac{1}{\alpha-1}}.$$

In particular, given a productivity level z, this equation pins down a net worth level $a^*(z)$ such that the firm is unconstrained for $a > a^*(z)$. □

These findings imply that firm exit is a function of both productivity and net worth: Firms with different configurations of these values will differ in their participation and exit choices. Therefore, we conclude that the standard model is generically at odds with the empirical patterns documented in the previous section, where financial factors are critical for exit, but where exit patterns do not systematically differ by productivity and size.

3.4 Extending model to account for empirical exit patterns

We now investigate how to reconcile the implications of the model for firm exit with the empirical patterns documented in the previous section. We ask: Under what conditions does the model imply that firm exit depends on net worth but is independent of firm-level productivity? In this section we show that this is the case if three conditions hold. The first condition is that variable costs are not paid upfront and, thus, are not subject to the financial constraint. In the context of our model, the first condition implies that $\nu = 0$. The next two conditions establish that fixed operation costs and credit constraints are proportional to firm-level productivity, $\phi(z) \propto z$ and $\theta(z) \propto z$.

The following proposition formalizes these statements:

Proposition 2. *If $\nu = 0$, $\theta(z) = \vartheta z$ and $\phi(z) = \varphi z$ for some $\vartheta, \varphi > 0$, then firm exit is determined by net worth a but is independent of productivity z.*

Then, under these three conditions, we find that the model's implications for firm exit become consistent with the empirical findings: Firm exit is critically determined by financial factors but is independent of productivity and scale. The proof is as follows:

Proof. The condition that $\nu = 0$ implies that the labor choice is always unconstrained, regardless of the value of a or z:

$$n = \left[\frac{w}{z^{1-\alpha}\alpha}\right]^{\frac{1}{\alpha-1}},$$

which means that profits are given as described above:

$$v(a,z) = zw^{\frac{\alpha}{\alpha-1}}(\alpha)^{\frac{\alpha}{1-\alpha}}(1-\alpha) - \phi(z)F.$$

Under the second condition, we have that $\phi(z) = \varphi z$, which implies that profits become:

$$v(a,z) = z\left[w^{\frac{\alpha}{\alpha-1}}(\alpha)^{\frac{\alpha}{1-\alpha}}(1-\alpha) - \mu F\right].$$

Having any active firms requires that $w^{\frac{\alpha}{\alpha-1}}(\alpha)^{\frac{\alpha}{1-\alpha}}(1-\alpha)-\mu F>0$. To the extent that this is the case, we have that firms choose to exit only if their net worth a is not sufficient to pay the fixed operation cost. Here, our final condition comes into play because firms exit if $\theta(z)a<\phi(z)F$, but Assumption 3 holds that $\theta\propto z$ and $\phi\propto z$. Thus, firms only exit if their net worth is sufficiently low; that is, if a is such that $\vartheta a<\varphi F$. Firms are otherwise active and do not exit. We then have that, in particular, firm-level productivity does not determine whether firms exit or not. □

These findings show that if variable costs do not need to be paid upfront and if fixed operation costs and financial constraints are proportional to productivity, the model's implications for firm exit are consistent with the empirical patterns documented in Section 2. In particular, under these conditions the model implies that firm exit is independent of productivity but is still determined by financial factors, as encoded by the financial constraint and the level of net worth a. In the rest of this section we argue that, indeed, the assumptions required to reconcile the model's implications with the data are reasonable.

Assumption 1: Fixed costs are increasing in productivity Fixed costs are costs that do not vary with short-term fluctuations in the level of output. However, while fixed costs are independent of the *current* production scale, the level of fixed costs incurred by a firm is often determined by the level of capacity, which is in-turn a function of productivity. Common examples of fixed costs include rent, property taxes, insurance, and salaries of employees with long-term contracts. While these are all likely to vary with firm productivity, they need not depend on the effective level of production. While there is no consensus in the literature on whether to model fixed costs as increasing in productivity, this is increasingly prevalent in recent studies (e.g., Midrigan and Xu 2014).

For another way to think about this assumption, consider that our model abstracts from expenditures in non-labor inputs that determine production capacity, such as capital or R&D. Instead, we interpret differences across firms along these other dimensions as captured by differences in productivity z. Then, fixed costs are indeed likely to scale up with productivity to the extent that productive firms are more likely to operate with a higher production scale, insofar that higher production capacity requires higher maintenance costs. This is likely to be the case: For instance, a productive firm may have higher fixed costs if it requires a large workforce to support its infrastructure and operations, regardless of the level of production. Thus, we interpret the assumption that fixed operation costs scale up with productivity as likely to capture how fixed costs scale with capacity.

Assumption 2: Variable costs are not finance-intensive Variable costs are expenses that change in proportion to the level of output or sales. These costs vary with the quantity of goods or services produced, and they include expenses such as direct labor costs and raw material costs.

Variable costs of operation may not be as finance-intensive as fixed costs. This is because variable costs can often be paid as they are incurred, rather than require large upfront payments. Additionally, variable costs are typically more flexible and easier to adjust in response to changes in demand or market conditions, which can help reduce the need for external financing. Therefore, we interpret the assumption that variable costs are not finance-intensive, required by our model to account for the empirical evidence, as a statement about the relative finance-intensity of variable costs vis-a-vis fixed costs. That is, this assumption captures the salient feature of U.S. firms that variable costs are less likely to be finance-intensive than fixed costs of operation. Indeed, this assumption is also consistent with recent studies, such as Bergin, Feng, and Lin (2021), who show that U.S. firms are more likely to be constrained in their financing of fixed costs relative to variable costs.

Furthermore, note that the finance-intensity of variable costs may also vary across industries and firm size. For example, in the service industry, where labor costs are a significant portion of variable costs, these costs may not be very finance-intensive, as they can be paid as employees work. However, it is important to note that even variable costs can be finance-intensive in some circumstances. For example, if a firm operates in an industry with high inventory costs, such as the manufacturing industry, then it may require significant working capital to finance these costs.

Assumption 3: Productive firms have better access to finance Assuming that firms' access to credit is a function of their productivity is consistent with both economic theory and empirical evidence. For instance, in standard models with endogenous borrowing constraints (e.g., Albuquerque and Hopenhayn 2004; Clementi and Hopenhayn 2006), lenders are able to provide productive firms with larger loans while mitigating the incentives to default due to either limited enforcement or asymmetric information. Empirical evidence supports this assumption as well. For instance, Beck and Demirguc-Kunt (2006) and Arellano, Bai, and Zhang (2012) show that access to finance differs systematically by firm size, with smaller firms relatively more distorted by frictions in financial markets than larger firms.

4 Conclusion

In this paper we investigate the role of financial factors in accounting for the dynamics of firm-level default during the Great Recession. We document a novel set of facts on the relationship between financial distress and exit rates. We interpret this evidence from the lens of a model with heterogeneous firms subject to financial frictions. Our findings suggest that credit constraints played an important role in accounting for the dynamics of firm-level exit during the Great Recession.

References

Albuquerque, Rui and Hugo A Hopenhayn. 2004. "Optimal lending contracts and firm dynamics." *The Review of Economic Studies* 71 (2):285–315.

Arellano, Cristina, Yan Bai, and Patrick J Kehoe. 2016. "Financial frictions and fluctuations in volatility." Tech. rep., National Bureau of Economic Research.

Arellano, Cristina, Yan Bai, and Jing Zhang. 2012. "Firm dynamics and financial development." *Journal of Monetary Economics* 59 (6):533–549.

Beck, Thorsten and Asli Demirguc-Kunt. 2006. "Small and medium-size enterprises: Access to finance as a growth constraint." *Journal of Banking & finance* 30 (11):2931–2943.

Bergin, Paul R, Ling Feng, and Ching-Yi Lin. 2021. "Trade and firm financing." *Journal of International Economics* 131:103461.

Buera, Francisco J, Joseph P Kaboski, and Yongseok Shin. 2011. "Finance and development: A tale of two sectors." *American economic review* 101 (5):1964–2002.

Chodorow-Reich, Gabriel. 2013. "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis." *The Quarterly Journal of Economics* 129 (1):1–59.

Chodorow-Reich, Gabriel and Antonio Falato. 2017. "The loan covenant channel: How bank health transmits to the real economy." Tech. rep., National Bureau of Economic Research.

Clementi, Gian Luca and Hugo A Hopenhayn. 2006. "A theory of financing constraints and firm dynamics." *The Quarterly Journal of Economics* 121 (1):229–265.

Crane, Leland Dod and Ryan Decker. 2019. "Business Dynamics in the National Establishment Time Series (NETS)/Leland Crane, Ryan Decker." .

Dinlersoz, Emin, Sebnem Kalemli-Ozcan, Henry Hyatt, and Veronika Penciakova. 2018. "Leverage over the Life Cycle and Implications for Firm Growth and Shock Responsiveness." NBER Working Papers 25226, National Bureau of Economic Research, Inc. URL `https://ideas.repec.org/p/nbr/nberwo/25226.html`.

Ebsim, Mahdi, Miguel Faria-e Castro, and Julian Kozlowski. 2023. "Credit and Liquidity Policies during Large Crises." *FRB St. Louis Working Paper* (2020-35).

Farboodi, Maryam and Péter Kondor. 2021. *Cleansing by tight credit: Rational cycles and endogenous lending standards*. LSE Financial Markets Group.

Gertler, Mark and Simon Gilchrist. 2017. "What happened: Financial factors in the Great Recession." Tech. rep., NYU, mimeo.

Gertler, Mark, Nobuhiro Kiyotaki, and Albert Queralto. 2012. "Financial crises, bank risk exposure and government financial policy." *Journal of Monetary Economics* 59:S17–S34.

Gorton, Gary and Guillermo Ordoñez. 2014. "Collateral Crises." *The American Economic Review* 104 (2):343–378. URL `http://www.jstor.org/stable/42920702`.

Gourinchas, Pierre-Olivier, Şebnem Kalemli-Özcan, Veronika Penciakova, and Nick Sander. 2021. "COVID-19 and small-and medium-sized enterprises: A 2021" time bomb"?" In *AEA Papers and Proceedings*, vol. 111. 282–86.

Khan, Aubhik, Tatsuro Senga, and Julia K Thomas. 2014. "Default risk and aggregate fluctuations in an economy with production heterogeneity." *Unpublished Manuscript* .

Kiyotaki, Nobuhiro and John Moore. 1997. "Credit cycles." *Journal of political economy* 105 (2):211–248.

Mian, Atif and Amir Sufi. 2009. "The consequences of mortgage credit expansion: Evidence from the US mortgage default crisis." *The Quarterly Journal of Economics* 124 (4):1449–1496.

Mian, Atif R and Amir Sufi. 2018. "Finance and business cycles: the credit-driven household demand channel." Tech. rep., National Bureau of Economic Research.

Midrigan, Virgiliu and Daniel Yi Xu. 2014. "Finance and misallocation: Evidence from plant-level data." *American economic review* 104 (2):422–458.