Firm Exit and Liquidity: Evidence from the Great Recession*

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July 2025

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 account for these facts.

JEL codes: E44, D22, L25
Keywords: firm exit, liquidity, credit constraints

*Contact information: fleibovici@gmail.com, wiczerd@gmail.com. We thank Matthew Famiglietti for excellent research assistance. We thank Kenneth Perez (Walls & Associates, LLC) for his assistance with the data, and we thank Teresa Fort for helpful comments. 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 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 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. This episode featured an aggregate drought of liquidity along with a deep recession and a sharp increase in firm exit. Figure 1 shows that the exit rate tripled from 2007 to 2008 at the same time as banks reported that they were tightening lending to both small and medium-to-large firms.[1] We ask: To what extent was the increase of firm exit during the Great Recession accounted for by liquidity rather than 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 conditions under which the model is consistent with our empirical findings.

Our findings point to the 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 like produc-

[1] Here and throughout the rest of the paper, the exit rate in year t is the share of firms active in January of year t that are not active in January of $t+1$.

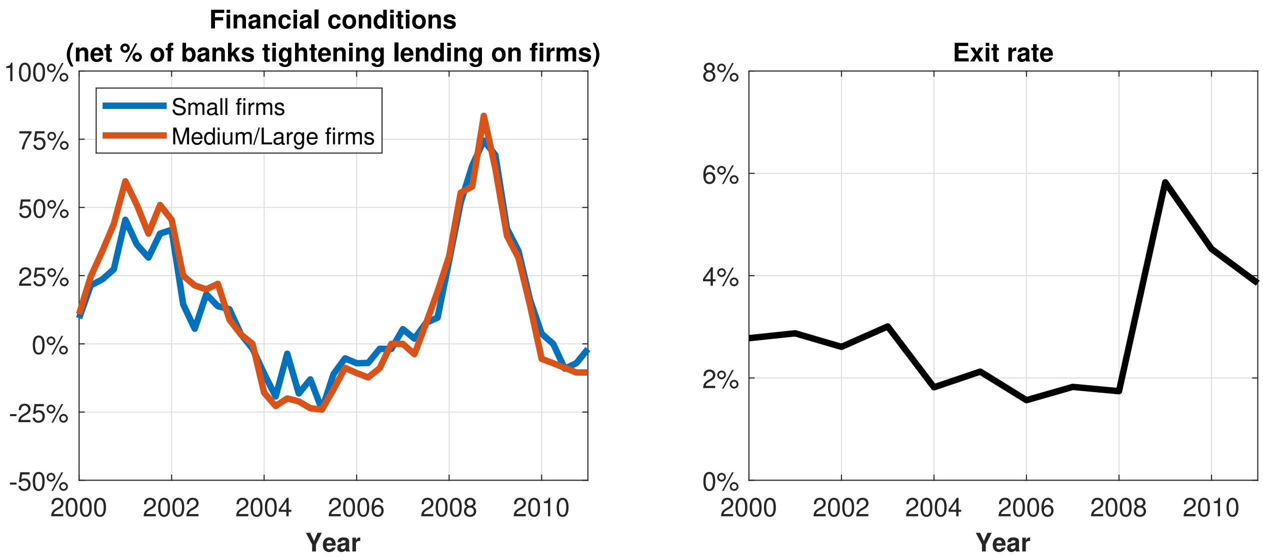


Figure 1: Great Recession, Financial Tightening, and Firm Exit

tivity, size, or age. In the aggregate, we find that firms in financial distress account for 30% of aggregate exit during this episode. These findings point to the importance of policies designed to mitigate liquidity issues during crises, as implemented in the U.S. during COVID-19.

We begin 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 and label firms in financial distress if they pay their vendors late. To ensure the reliability of our dataset, we benchmark key statistics against official sources from the U.S. Census and U.S. Courts, validating the representativeness of our sample. We document three key findings. First, we observe a systematic relationship between firm exit rates and financial distress: Firms that pay their vendors late have much higher exit rates. Second, differences in firm exit rates by financial distress increased substantially during the crisis. Finally, these differences in firm exit rates by financial distress played an important role in accounting for the increase in the aggregate exit rate during this episode.

While these features of the data suggest that there is a 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 low-demand goods might struggle to pay their vendors while also featuring high rates of exit. 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.

To validate our interpretation that liquidity constraints were a critical factor driving firm exit during the Great Recession, we conduct an additional empirical test that leverages variation across industries in firms' reliance on trade credit. If financial distress played a causal role in driving firm exits, then we would expect firms in industries with greater trade credit intensity (TCI) to be disproportionately affected during the liquidity shock associated with the crisis. Using a triple-difference approach, we find evidence consistent with this hypothesis: firms with poor financial standing in industries with high trade credit intensity experienced a 5 percentage point higher increase in exit rates during the Great Recession compared to firms in industries with low TCI. This result provides further support for a causal interpretation of the relationship between financial distress and firm exit.

We interpret these findings through the lens of a mostly standard, tractable model of firms with endogenous exit decisions and financial constraints. Firms are heterogeneous in productivity and access to liquidity. To operate, firms have to pay a fixed operation cost and are subject to a financial constraint requiring them to pay a fraction of their costs upfront. These payments are financed through internal funds, and 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 liquidity? Generically, the model implies that firms' operation decisions are jointly determined by both productivity and the amount of liquidity available. In the model, given a level of productivity, higher liquidity increases firms' operation scale and the likelihood that they will find it profitable to operate. Similarly, given a 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 productivity and liquidity jointly determine exit contrasts to our empirical findings. Thus, we investigate conditions that can reconcile the model's implications for the determinants of firms' operation decisions. We find three conditions such that liquidity factors but not productivity determine exit: (*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. It is like a zero-profit condition but applying to exit. Condition (*iii*) implies that firm productivity alleviates financial constraints, consistent with the implications of various micro-founded theories of these frictions. Under these assumptions, firms' operation decisions are no longer determined by firms' productivity and instead, only by liquidity.

Conditions (*i*) and (*ii*) emphasize 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. These conditions are consistent with often-cited 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 investigating 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 (2019), 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 with 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 (2023) 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 (2022) 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 (2018) 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 extent to which firms' access to finance shaped exit dynamics during the Great Recession. We leverage a novel dataset that covers the universe of U.S. establishments and includes detailed measures of firm-level financial constraints. We begin by describing the construction of this dataset and benchmarking its representativeness against standard sources. Then, we use its unique measure of financial distress to document the significant relationship between firms' liquidity positions and their exit probabilities during the crisis. Finally, we compare the impact of financial constraints to other factors commonly associated with firm exit, such as productivity, size, and age.

2.1 Data

Our 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. 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 aggregate to 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 them into firms if they share headquarters. 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.[2] Then, we aggregate the dataset to the firm level by identifying all establishments with a common headquarters into a 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. Note that the findings reported in the paper are robust to examining the data at the establishment level.

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.

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

Credit ratings, delinquency, and financial distress The most important financial variable is the credit rating, Paydex scores, which characterizes the timeliness of an establishment's payments to suppliers. 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 whether to provide loans and credit to an establishment.

The Paydex score of an establishment ranges from 0 to 100 and reflects the timeliness of its payments to suppliers. A score below 50 indicates payments are at least 30 days overdue, with even lower scores corresponding to longer delays; for instance, a score between 1 and 19 reflects payments over 120 days late. Conversely, a score of 80 indicates payments made on time, and a score of 100 is assigned to establishments paying at least 30 days early. To be assigned a Paydex score, Dun & Bradstreet requires an establishment to have information on at least four vendor payments.[3]

The NETS database reports each establishment's minimum and maximum Paydex scores each year and we use their minimum. 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 establishments' minimum Paydex scores by the number of employees across the different establishments.

We partition firms into two groups, financial distress and good standing, where the former was delinquent at least 30 days that year, as indicated by a minimum Paydex score below 50. Our findings are robust to alternative cutoffs and using three-year prior status.

Firm-level exit: NETS vs. BDS vs. Bankruptcies Before we study the link between financial distress and firm-level exit, we show that the information on exit in the NETS is

[3]For more information, see `https://docs.dnb.com/static/doc-uploads/supplier/en-US/support/FAQs.pdf`.

consistent with other public data sources.[4] To do so, we focus on (*i*) the Business Dynamics Statistics (BDS) produced by the U.S. Census Bureau from their Longitudinal Business Database and (*ii*) business bankruptcies as reported by U.S. Bankruptcy Courts.[5]

We begin by contrasting NETS with the publicly available firm-level tabulations of the BDS. While the BDS and NETS are both designed to cover the universe of establishments in the US, the entry and exit dynamics may meaningfully differ. As in Haltiwanger, Jarmin, and Miranda (2013) and Ding, Fort, Redding, and Schott (2022), a firm is only counted as exiting if economic activity stops at the physical location of all its establishments. This is a stricter definition than the NETS, for example in the case of reorganizations.[6] Thus, we see more in-and-out churn in the NETS data.[7]

Despite the differences, we can benchmark firm dynamics in NETS to the BDS, focusing on a statistic that can be more comparably measured in both: the number of active firms. Figure 2 compares the growth in the number of firms, normalizing the level to 2007. In both, we restrict the sample similarly to those with at least 10 employees at the firm and to establishments with a known firm linkage. The NETS-based firm dynamics show a slightly larger and more abrupt decline than the BDS. Timing differences between the two surveys partly account for this, as each measures a firm's operation at different points in the year.[8]

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

[5]There are many other sources of firm-level data. For instance, one could also compare this to exits in Compustat, but that is a very different sampling frame. NETS captures the universe of firms and establishments, for which the BDS is the best benchmark. Compustat looks at the small subset of large, publicly listed firms and our findings are robust to restricting attention to private firms, so showing consistency with the Compustat subsample would not validate our results.

[6]Specifically, the codebook defines a firm-level exit in the BDS as follows: "Count of firms that have exited in their entirety during the period. All establishments owned by the firm must exit to be considered a firm death. This definition of firm death is narrow and strictly applied so that a firm with 100 establishments would not qualify as a firm death if 99 exited while 1 continued under different ownership. Note firm legal entities that cease to exist because of merger and acquisition activity are not classified as firm deaths in the BDS data." See `https://www.census.gov/content/dam/Census/programs-surveys/business-dynamics-statistics/codebook-glossary.pdf` and `https://www.census.gov/programs-surveys/bds/documentation/methodology.html` for more details.

[7]NETS may also feature higher entry and exit rates because of sample churn, i.e. a continually operating establishment might occasionally cease to be collected by D&B. In discussions with the designers of the NETS database, we confirmed that our subsample should be largely clean of these erroneous exits.

[8]In particular, NETS is measured around the start of each calendar year, while the BDS is measured toward

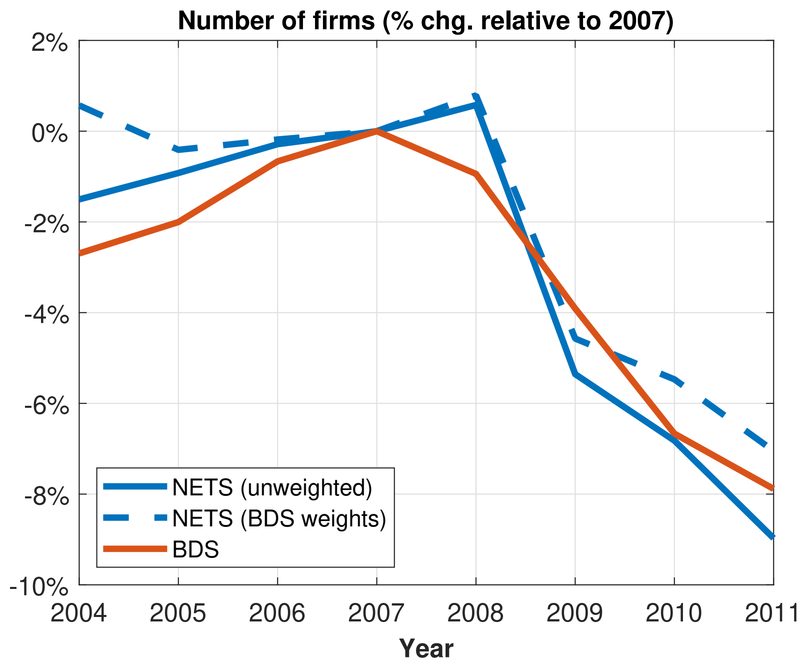


Figure 2: Firms growth: NETS vs. BDS

But overall, the similarities are striking: between 2004 and 2007, the number of firms in both data sets increased by about 2%. Then from this peak, they declined by just under 8% in BDS and just over 9% in the NETS.

We also re-weighted the NETS firms by size and industry bins to mimic the cross-sectional distribution in the BDS.[9] This is shown in the dotted blue line and is remarkably similar to the unweighted sample. The underlying reason that we do not see particularly different dynamics reflects the economics we explore below, that many of the often-observed factors on which we would weight are not particularly important in accounting for exit around this episode.

Business bankruptcies provide another useful benchmark to assess the reliability of firm exit rates observed in NETS. Compared to the BDS, bankruptcy data captures firm closures more consistently with the NETS definition. However, bankruptcies still represent a narrower measure, as not all firm exits involve a formal bankruptcy filing. Nevertheless, if

the end of the first quarter of each year.

[9]See Section 1 of the Online Appendix for a detailed comparison of the representativeness of NETS relative to BDS.

the proportion of exiting firms that declare bankruptcy remains stable over time, changes in bankruptcy rates should closely reflect changes in the overall firm exit rate.

We use data from U.S. Courts on Chapter 7 bankruptcy filings during the financial crisis and compare it to prior years, from 2001-2007. The long base period smooths over legal changes in the bankruptcy code. Chapter 7 business bankruptcy filings involve the liquidation of a debtor's assets, a shutting down that would look like an exit in NETS.[10] Bankruptcy was 179.1% higher in 2008-2010 than in the base period. We compute the analogous statistic in NETS and find the extent of exit over this period relative to the base is strikingly similar: Exits in the NETS were 176.2% higher in 2008-2010 than the 2001-2007 average.

2.2 Summary statistics

In this section, we contrast summary statistics between firms in good financial standing and firms in financial distress.

The top panel of 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 more productive, older and larger in both sales and number of workers 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. Panel B of Table 1 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

[10] Other common types of bankruptcies, like Chapter 11, are less suitable for our purposes given they involve firm reorganization, with continuing operations.

Panel A: Summary Statistics		
	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

Panel B: Transition Probabilities			
$t \setminus t+1$	Good standing	Financial distress	Exit
Good standing	0.938	0.036	0.029
Financial distress	0.261	0.655	0.069

Table 1: Firm characteristics by financial standing, Avg. 2006-2012

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 on being in financial distress in period t, 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, Panel A of 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 impact of financial distress and these other covariates in the following sections.

2.3 Financial factors and firm exit

Next, we examine firm-level exit rates and financial distress, measured using Paydex scores. The left panel of Figure 3 contrasts the dynamics of firm-level exit rates between firms in

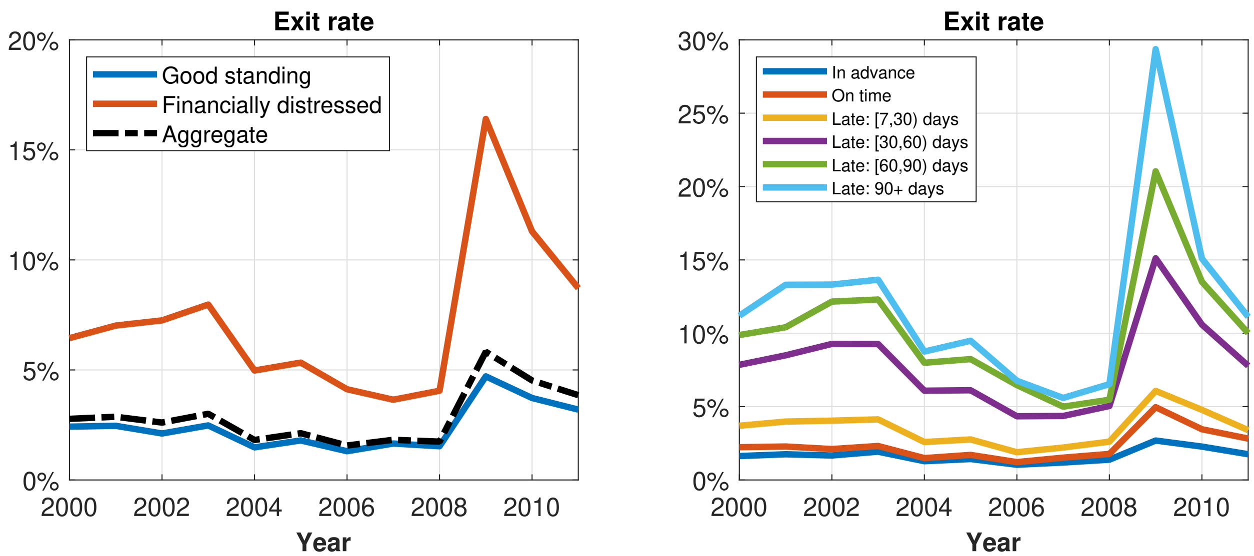


Figure 3: Firm-level financial position and exit rates

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 aggregate exit rate. Throughout the entire sample period, firms in financial distress exhibit consistently higher exit rates—by at least 2 percentage points—and experience a substantially larger spike in exit rates during the recession relative to firms in good standing.

The right panel of Figure 3 disaggregates firm-level exit rates across finer categories of financial status. As in the left panel, firms' exit rates depend systematically on their financial position, monotonically decreasing with Paydex scores. There is a discrete break between those more than or less than 30 days late, our cutoff for financial distress. 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.

The substantial increase in exit rates among firms with a weak financial position also affected the dynamics of firm-level exit in the aggregate, as we detail further below. 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. The two exit rates diverge in 2008 because of the substantial increase in exit among firms in financial distress.

2.4 Firm exit: Financial vs. other factors

We now contrast financial distress to other characteristics like firm size, productivity, and age. These are characteristics that previous studies suggested play an important role in accounting for firm-level exit rates. We measure firm size by number of workers and sales, and proxy productivity as sales per worker.

Unconditional relations Figure 4 plots firm exit rates by (*i*) number of workers, (*ii*) sales, (*iii*) sales per worker, and (*iv*) age. These exit rates are unconditional, illustrating raw correlations without controlling for other firm-level characteristics. The observed patterns are largely as expected: firms that are older, larger, or more productive (higher sales per worker) have lower exit rates during the crisis.

Importantly, we maintain the same vertical scale as in Figure 3 to facilitate comparisons. Strikingly, these non-financial characteristics are associated with notably smaller differences in exit rates compared to financial distress as measured by Paydex scores. Thus, although previous studies emphasize these firm attributes as key determinants of exit, we find that financial constraints played a relatively more significant role in driving firm exit during the Great Recession.

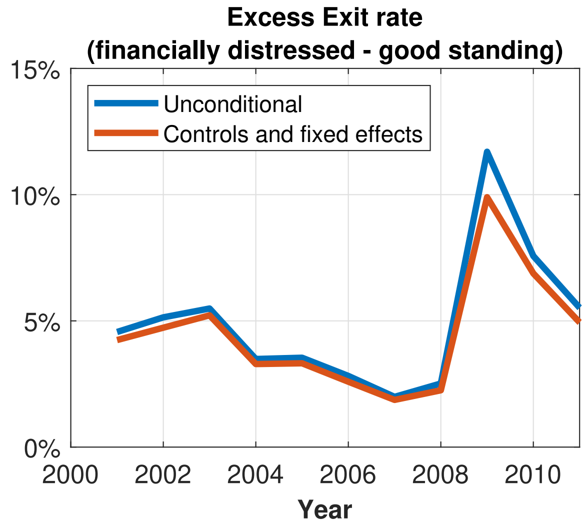
Regression analysis We now investigate whether the differences in firm-level exit by financial position documented in Figure 3 are robust to controlling for the observables examined in Figure 4. To do so, we estimate a regression specification in which firm-level exit in period t is explained by financial position and these additional firm-level observables. We

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

estimate:

$$\begin{aligned}\text{Exit}_{it} = &\sum_{j=2001}^{2011} \beta^j \times \text{Financially distressed}_{it} \times \text{Year}_{it}^j + \sum_{k=1}^{4}\sum_{j=2001}^{2011} \alpha^{jk} \times \text{Age}_{it}^k \times \text{Year}_{it}^j + \\ &\sum_{k=1}^{5}\sum_{j=2001}^{2011} \gamma^{jk} \times \text{Sales per worker}_{it}^k \times \text{Year}_{it}^j + \sum_{k=1}^{5}\sum_{j=2001}^{2011} \eta^{jk} \times \text{Workers}_{it}^k \times \text{Year}_{it}^j + \varepsilon_{it},\end{aligned}$$

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_{it}^k is an indicator that is equal to 1 if the firm belongs to age group k. $\text{Sales per worker}_{it}^k$ is an indicator that is equal to 1 if the firm's sales per worker belongs to group k. Workers_{it}^k is an indicator that is equal to 1 if the firm's number of workers belong to group k. Year_{it}^j is an indicator that is equal to 1 if $j = t$. Note that firms' classification into groups based on age, sales per worker, and



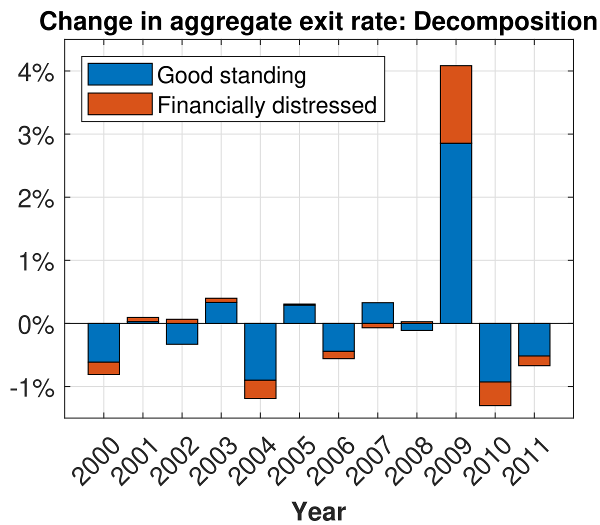


Figure 5: Financial distress and aggregate firm exit

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.

Our primary coefficients of interest are β^j, which capture the interaction between financial distress and year indicators. These coefficients, which we refer to as *excess exit rates*, measure the difference in exit probabilities between firms in financial distress and those in good financial standing, conditional on other firm characteristics.

The left panel of Figure 5 plots the excess exit rates estimated with and without additional controls and fixed effects. Controlling for these observables reduces the estimated excess exit rate somewhat, as expected given their correlation with both financial distress and exit. Nevertheless, the reduction is modest, underscoring that financial distress remains the dominant factor driving excess exit. Thus, even after controlling for various observables and fixed effects, financial distress remains quantitatively the most significant determinant of excess exit rates.

To further illustrate the robustness of our results and quantify the effect of including different controls and fixed effects, Table 2 reports detailed estimation results from four alternative specifications of our regression. Column 1 presents estimates from the simplest model, without controlling for age, size, or productivity (i.e., unconditional). Column 2

	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 2: Excess exit rate of delinquent firms: Regression analysis

introduces these additional controls, interacting them with year indicators. Columns 3 and 4 then repeat these two specifications but add county and industry fixed effects. Consistent with our earlier discussion, the estimates show a modest reduction in excess exit rates when adding controls, reinforcing our conclusion that financial distress remains the primary driver. Given that all interaction terms between financial distress and year indicators are statistically significant at the 1% level, we omit standard errors to simplify the exposition.

2.5 Instrumenting with Trade Credit Dependence

To strengthen the causal interpretation of financial distress on firm exit, we exploit cross-industry variation in exposure to liquidity shocks, following the approach of Rajan and Zingales (1998). Our measure of financial distress, the Paydex score, directly captures firms' standing with their trade-credit counterparties. Thus, we construct an industry-level measure of trade credit intensity (TCI), reflecting firms' reliance on trade credit financing. Our hypothesis is that liquidity shocks should disproportionately affect firms operating in industries with high TCI, as these firms inherently depend more on maintaining good standing in trade credit relationships. Since TCI reflects predetermined industry-level financing practices, it provides exogenous variation in firms' exposure to liquidity disruptions, helping us isolate the causal impact of financial distress on firm exit.

For this exercise, we use Compustat data to construct our industry-level TCI measure. Specifically, we define TCI as accounts payable divided by assets, following Fisman and Love (2003), and assign industries their TCI based on the median firm-year observation within each three-digit industry code, pooling data from 1985–1997. An advantage of our analysis is that the NETS database captures exit dynamics for a broad set of firms beyond the publicly traded firms typically covered by Compustat. However, since NETS lacks detailed financial variables needed to compute TCI, we rely on Compustat as an industry-level proxy. Thus, a key assumption underlying our approach is that publicly listed Compustat firms share similar trade credit practices with privately held firms within narrowly defined industry codes.

Differences in TCI across industries allow us to assess whether the Great Recession's liquidity shock causally impacted firm exit. The intuition is that firms in industries with high TCI should experience a disproportionately larger increase in exit rates in response to the same liquidity shock. As long as other determinants of firm exit are not systematically correlated with TCI, comparing exit rates across high- and low-TCI industries isolates the causal effect of financial constraints. This identification strategy parallels the logic used by Rajan and Zingales (1998), who leverage cross-industry variation in financial dependence to identify the effect of financial shocks.

Specifically, we estimate the following regression to quantify how the impact of financial distress on firm exit rates varies by industry-level trade credit intensity (TCI) year-by-year:

$$\begin{aligned}\text{Exit}_{it} = \alpha &+ \sum_{j=2001}^{2011} \beta^j \left(\text{Financially distressed}_{it} \times \text{HighTCI}_i \times \text{Year}_{it}^j\right) \\ &+ \sum_k \sum_{j=2001}^{2011} \gamma^{jk} (Z_{it}^k \times \text{Year}_{it}^j) + \eta_i + \eta_t + \varepsilon_{it}\end{aligned}$$

where Exit_{it} is an indicator variable equal to one if firm i exits between period t and $t+1$. The variable $\text{Financially distressed}_{it}$ equals one if firm i is financially distressed in year t. HighTCI_i indicates industries with trade credit intensity more than one standard deviation above average or less than one standard deviation below average. Year_{it}^j are year indicators. The coefficients of interest, β^j, capture how financial distress affects exit rates differently for firms in high-TCI industries in each year. Controls Z_{it}^k include firm-level characteristics such as age, size, and productivity, interacted with year indicators. Firm or industry fixed effects η_i and year fixed effects η_t are included, and ε_{it} is the error term.

To implement our approach, we classify industries into high- and low-exposure groups based on their TCI. Specifically, industries with TCI more than one standard deviation above average (above 13.0%) are considered highly exposed, while those with TCI more than one standard deviation below average (below 3.8%) are considered unexposed. Figure 6 plots firm exit rates for these two groups, further split by firms' financial standing. As expected, firms in good financial standing exhibit relatively similar exit rates regardless of TCI, reflecting their continued access to trade credit. In contrast, among financially distressed firms, those in high-TCI industries consistently have higher exit rates compared to those in low-TCI industries. Moreover, these differences widen considerably during the Great Recession. Using a triple-difference calculation, we find that financially distressed firms in high-TCI industries experienced a 5 percentage point greater increase in their exit rates between 2008-2010, relative to their counterparts in low-TCI industries, underscoring

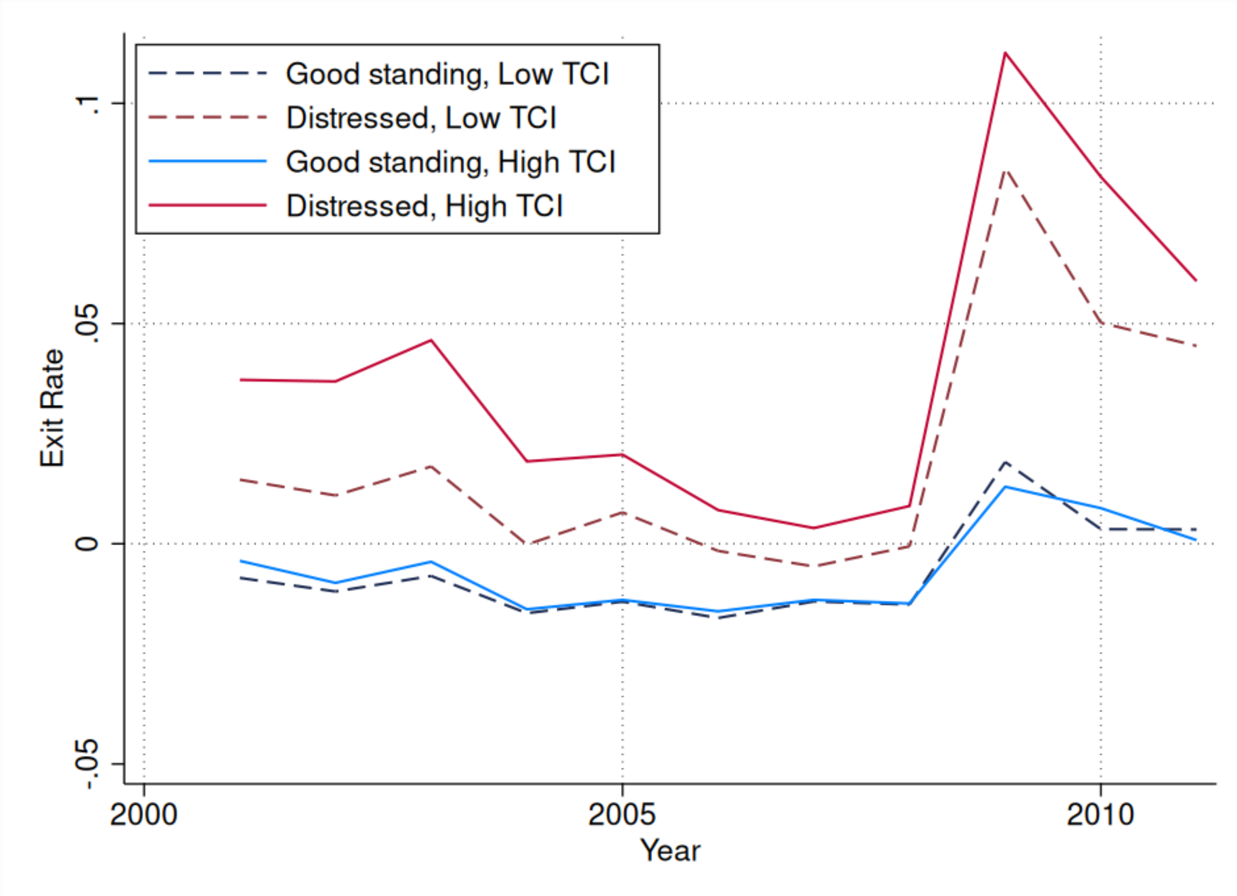


Figure 6: Firm Exit Rates by Trade Credit Intensity and Financial Standing

the amplified impact of the liquidity shock where trade credit is more critical.

2.6 Aggregate exit rate decomposition: Role of financial factors

The previous findings show quantitatively and statistically significant differences in exit rates between firms in financial distress and good financial standing during the Great Recession. Then, we ask: To what extent does this relatively small set of firms drive the aggregate increase in exit?

To answer this, we linearly decompose the contribution to the aggregate exit rate from firms in financial distress and those in good standing. We show the exit rate can be changed into an expression of the size of each of these groups and their exit rate.

Beginning generically, consider 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:

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

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 $j = 1, \ldots, J$ as follows:

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

where Δ denotes the first difference operator, which we use here to denote the difference between periods t and $t-1$.

We partition firms into two groups based on their financial position. Then, with Equation 1, we decompose the contribution of financially distressed firms to the increase of the aggregate exit rate during the Great Recession.

In the right panel of Figure 5, we show this linear decomposition of the aggregate exit rate into the contribution of firms in financial distress and firms in good financial standing. For instance, in 2009 the aggregate exit rate increased by approximately 4.1 percentage points, of which 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 contribute disproportionately 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. These firms also contributed to the subsequent decline of the aggregate exit rate in the crisis' aftermath because of a decline of their exit rates rather than a decline in the share of distressed firms.

2.7 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. We find 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. We ask: To what extent can a standard model with heterogeneous firms facing credit constraints account for these? To answer, we write a simple, tractable model to clarify the determinants of firms' exit decisions, and what conditions must hold to elevate financial factors over others like

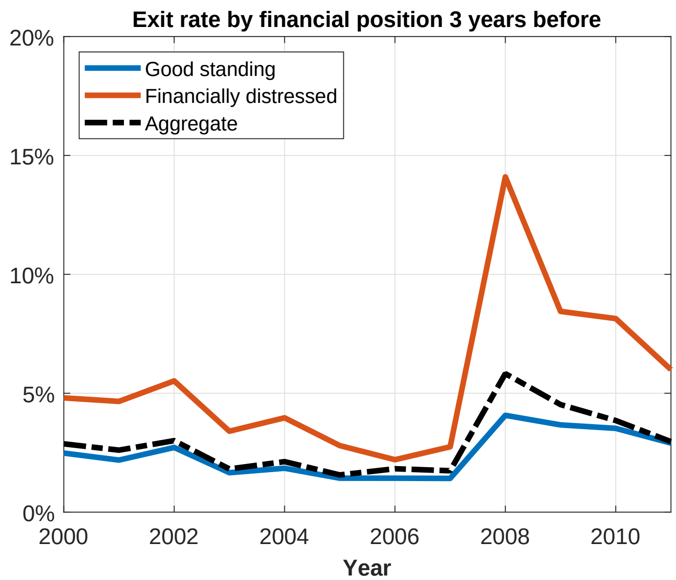


Figure 7: Firm-level financial position and exit rates: Alternative definition

productivity or size.

3.1 Setup

We consider an economy with 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 whose price is the numeraire. 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 $\phi(z)F > 0 \forall z$ 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 captures the extreme case where fixed operation costs are independent of firms' idiosyncratic productivity and the more general case 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, allowing them to borrow $\theta(z)$ units of the good per unit of net worth. These loans are intratemporal, 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.[11]

Firms maximize profits and the timing is as follows: Firms first choose whether to operate and then choose the amount of labor to hire. 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:

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

[11] Another way to think of the constraint is that it models the maximum amount that banks are willing to lend to firms as a multiple of their net worth.

where we have:

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

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. 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.

Given the static nature of the model, we interpret firms' decisions 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?

This static analysis represents exit rates by taking a set of firms operating given a set of financial and productivity realizations and then considering their operating decisions. Hence, exit is the difference between firms coming into the period with a particular state and the ones that chose not to operate.

3.3 Productivity and finance jointly determine exit

We begin by investigating the model's determinants of firm exit. We find that:

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

That is, firm exit depends on both productivity z and the extent to which firms have access to finance $\theta(z)a$.

Proof. Firms exit if $v(a, z) < 0$. Then, the proof shows 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.

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

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

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:

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

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 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 $a > a^*(z)$. $\square$

These findings imply that firms with different levels of productivity and net worth will differ in their participation and exit choices. Therefore, this unrestricted model is generically at odds with our empirical patterns, where financial factors are critical for exit, but exit does not systematically differ by productivity and size.

3.4 Extending model to account for empirical exit patterns

We now reconcile the implications of the model with the patterns in Section 2. Under what conditions does the model imply that firm exit depends on net worth but not firm-level productivity? This is the case if three conditions hold. First, that variable costs are not paid upfront and are not subject to the financial constraint. In the context of our model, this is $\nu = 0$. 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.*

Under these three conditions, firm exit is determined by financial factors but is independent of productivity and scale. The proof is:

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, if $\vartheta a < \varphi F$. In this condition, firm-level productivity does not determine whether firms exit. $\square$

We presented three conditions such 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 these assumptions are reasonable.

Assumption 1: Fixed costs are increasing in productivity Fixed costs do not vary with short-term fluctuations in the level of output, independent of the *current* production scale. But, 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. For example, rent, property taxes, insurance, and employee salaries with long-term contracts are all fixed costs likely to vary with firm productivity but not the production level. Further, modeling fixed costs as increasing in productivity is increasingly prevalent (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 likely to scale up with productivity because productive firms are generally larger and higher production capacity requires higher maintenance costs.

Assumption 2: Variable costs are not finance-intensive Variable costs change in proportion to the level of output or sales, which are generally not as finance-intensive as fixed costs because they can often be paid as they are incurred. The idea is that variable costs are more flexible and easier to adjust in response to changes in demand or market conditions, reducing the need for external financing. Making variable costs entirely independent of finance is a stark way to contrast them with fixed costs. 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 than of variable 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 can 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.

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Appendix: Data setup and weighting

In this section, we provide a more detailed description of the setup of the NETS data and how we use the BDS for weights. The major difficulty is that the NETS database is essentially a convenience sample, albeit a very large one. Being derived from Dun & Bradstreet firm ratings means that nearly any business entity that needs to do business with another business must be in its universe. This is, however, potentially too broad as it will also include many that operate at a scale smaller than most economic notions of a firm.

Our chief sample selection criterion is to exclude small firms. By selecting firms that have greater than 10 employees, we are getting a more reliable subsample. The advantage of using these larger firms is two-fold: first they are more consistent with what we think of as a firm in our model: excluding secondary employment and very small operations that probably do not require financing. Second, and more importantly, larger firm observations are double-checked by Walls and Associates, the creators of the NETS, particularly to minimize sample churn. That is, they validate the entry/exits to ensure the longitudinal dimension is not corrupted by firms artificially entering and exiting the D&B dataset.

Of course, because the sample is not drawn either to be representative or to necessarily cover the exact universe of firms, it maybe not be representative along certain key dimensions that are correlated with our outcome-of-interest, exit. The best dimensions on which we can reweight are age, size and sector. We choose not to use age to weight because it is not reliably measured in either BDS or NETS and because the definition of when the firm “started” could meaningfully differ across the datasets. In the BDS, age is left-censored by the start of the LBD. In the NETS, it is self-reported and often has observable inconsistencies. Further, the BDS age begins when the firm hires an employee, whereas in NETS it is when operations begin.

Size and sector can get us fairly far, however. For each of the detailed size and sector cells reported in the BDS, we compute the fraction of employment in that cell in the NETS.

We use the joint distribution to create weights, for an observation in NETS with sector k and size bin g $\frac{f_{k,g}^{BDS}}{f_{k,g}^{NETS}}$.

The marginal employment distributions for these two dimensions are in Table 3. Note that these distributions sometimes differ, for instance manufacturing, NAICS code 31-33, is over-represented in the NETS, probably because nearly all of these firms need to have trade linkages and therefore utilize D&B. However, because exit dynamics during the recession are not particularly strongly affected by weighting, these differences do not affect our outcomes much.

Size	BDS	NETS	NAICS code	BDS	NETS
10 to 19	0.08	0.07	11	0.00	0.01
20 to 99	0.20	0.22	21	0.01	0.01
100 to 499	0.16	0.15	22	0.01	0.01
500 to 999	0.06	0.05	23	0.05	0.04
1000 to 2499	0.08	0.08	31-33	0.14	0.20
2500 to 4999	0.06	0.06	42	0.05	0.04
5000 to 9999	0.07	0.06	44-45	0.13	0.11
10000+	0.30	0.30	48-49	0.04	0.04
			51	0.03	0.03
			52	0.06	0.07
			53	0.02	0.02
			54	0.06	0.06
			55	0.03	0.01
			56	0.07	0.06
			61	0.02	0.00
			62	0.13	0.12
			71	0.02	0.02
			72	0.09	0.08
			81	0.05	0.04

Table 3: Category sizes in BDS and NETS

The result is that our re-weighed exit rate reduces its peak somewhat. In the main text we show that this makes the overall decline in the stock of firms even more closely resemble the dynamics of the BDS. We show the weighted and unweighted exit rates in Figure 8, which shows about a 1 pp discrepancy during the crisis. For our main analysis, we do not weight because, the difference is not particularly large and because it is not obvious that the BDS should be the standard for our analysis.

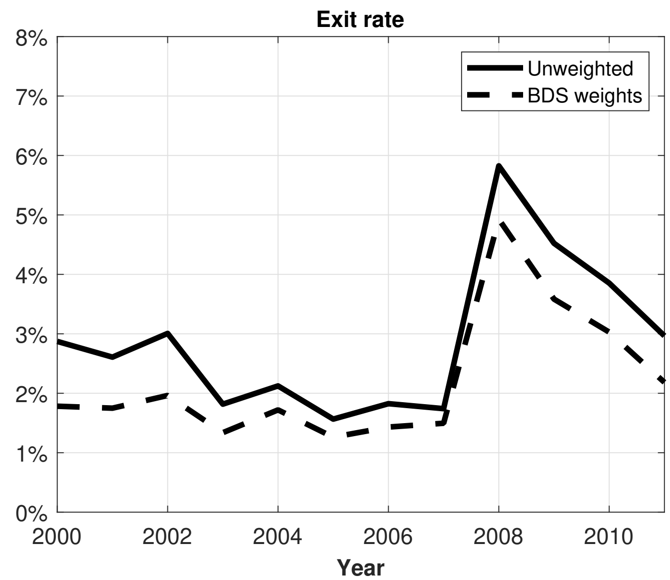

Figure 8: Aggregate exit rate: Unweighted vs. BDS weights