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Leverage over the Firm Life-Cycle, Firm Growth, and Aggregate Fluctuations
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ABSTRACT

We create a novel dataset by merging the Census Bureau's Longitudinal Business Dynamics data with firm-level financial information from Moody's-Orbis. We find that firm leverage varies over a firm's life-cycle, acting as a binding constraint only in certain times. As a result, the impact of a financial shock on employment depends on where firm is in its life-cycle at the onset of the shock. While highly leveraged small firms accounted for 3% of total U.S. employment, their employment response contributed up to 5% of excess job losses during Great Recession.

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Much is known about U.S. firms' growth over their life-cycle, yet there remains a significant gap in understanding how these firms finance their growth and navigate financial challenges. Closing this knowledge gap is important for assessing the effects of firm financing on aggregate employment growth. This knowledge gap primarily stems from the absence of comprehensive data matching the financial and real outcomes of U.S. businesses. Given that privately-held firms are not obligated to disclose their financial positions, much of what is known about firm financing pertains to publicly-traded companies.[1]

Privately-held firms, however, constitute a vital component of the U.S. economy, accounting for 75% of aggregate employment and 54% of aggregate gross output on average over the past two decades. Small-young firms, which account for 20% of U.S. employment and are primarily privately owned, play a pivotal role in fostering business dynamism and job creation (e.g., Fort, Haltiwanger, Jarmin and Miranda (2013)). Theoretical research indicates that financial constraints and debt burden can impede the growth of these smaller, younger businesses—–as is typically modeled using borrowing constraints that are dependent on firm size and age. Any tightening of credit conditions could potentially generate a significant adverse impact on the overall economy by affecting this dynamic segment of firms (e.g., Gertler and Gilchrist (1994), Cooley and Quadrini (2001), Cooley, Marimon and Quadrini (2004), Albuquerque and Hopenhayn (2004), Khan and Thomas (2013), Virgiliu and Xu (2014), Buera and Moll (2015)), although systematic evidence connecting micro and macro theories is lacking.

Our paper provides comprehensive evidence on the heterogeneity of financial constraints over firms' life-cycle and the implications of such heterogeneity for aggregate employment growth. We do this by linking financial constraints of U.S. firms to their employment growth through a novel dataset that integrates the balance sheets of both publicly-traded and privately-held firms with their employment over time. Our findings highlight significant variation in financial constraints across and within firms over the

[1]The main source of these data is corporate tax records that individual researchers have no access. This is also true for institutions. The Federal Reserve's Flow of Funds, a widely used data source for aggregate corporate sector debt, also does not have access to tax records and hence is not constructed from the ground-up, but rather based on estimates from the filings of the financial sector.

life-cycle that is systematically related to firm growth.

We use firm leverage as a measure of financial constraints as this choice is grounded in the extensive theoretical and empirical literature (e.g., Bernanke and Gertler (1989), Bernanke, Gertler and Gilchrist (1999), Ottonello and Winberry (2020), Rajan and Zingales (1995)). As a firm's leverage is endogenous to its employment growth, we use the 2008 episode of the Great Recession as an exogenous shock to *all* firms' credit conditions so that we can study the heterogeneous employment response of firms when they face the shock with different levels of leverage. Using these well-identified micro estimates of firm leverage on firm growth, we also quantify the aggregate impact of heterogeneous financial frictions across firms on U.S. employment growth. Our central finding underscores that highly-leveraged small firms, particularly young ones, deleverage significantly when confronting aggregate credit shocks, leading to diminished employment growth compared to their counterparts. This reduced growth among highly-leveraged small and young firms disproportionately contributes to aggregate job losses during economic downturns like the Great Recession.

Our new dataset combines detailed information on firm financing and outcomes using several sources. Balance sheet information comes from Standard & Poor's Compustat database for publicly-traded companies, and Moody's Orbis dataset for privately-held ones. For firm employment and age, and for other firm characteristics such as revenue, industry, and location, we use the Census Bureau's Longitudinal Business Database (LBD). We refer to this new dataset as LOCUS, an acronym that reflects the combination of the LBD, "L", Orbis, "O", and Compustat, "C", for the United States, "US". The LOCUS dataset has three key features that enable us to better study the relationship between firm dynamics and financial constraints over the firm life-cycle: (i) better representation of the overall firm size distribution, (ii) information on both firm age and size (measured by employment, sales and assets), and (iii) detailed balance sheet data (debt, equity, maturity) for both publicly-traded and privately-held firms.

An important contribution of our paper is better representation of the U.S. firm population using a dataset that provides both firm-level real and financial outcomes. Figure 1 demonstrates how the LOCUS dataset improves the representativeness of firm size, measured by employment. The firm size distribution becomes more similar to the distribution of the universe of U.S. employer businesses (LBD) as we move from publicly-traded firms (Compustat) to privately-held firms in LOCUS. It is well known that the reporting of financial information is voluntary in Orbis. An additional contribution of LOCUS is that it provides propensity-score weights based on the universe of firms in the LBD to account for the selection generated by this voluntary financial reporting, which, as we show below, further improves the representativeness of the raw (unweighted) LOCUS data shown in Figure 1. Our empirical analysis uses weighted data—Figure 1 is for illustrative purposes.

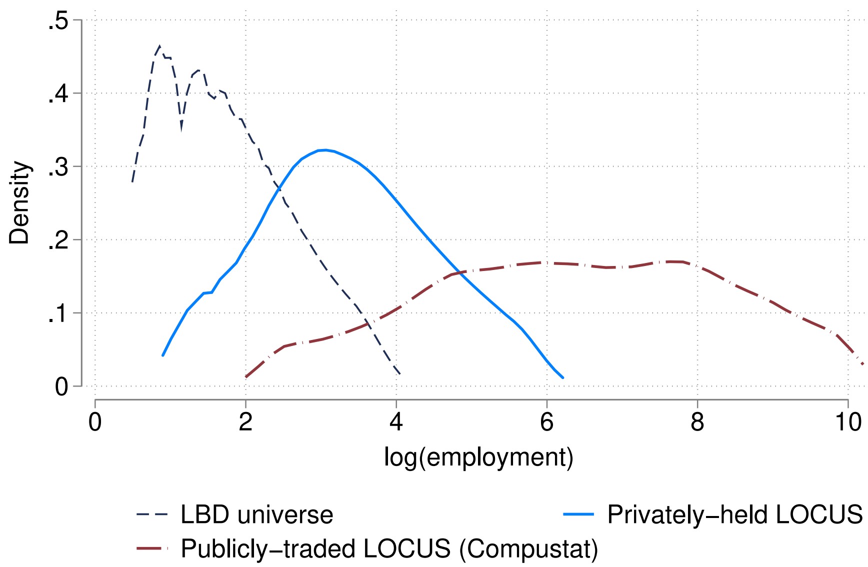


Figure 1: LBD and LOCUS Employment Distributions

Notes: Plots the distribution of firm-level log (employment), among firms in the LBD, privately-held firms in LOCUS, and publicly-traded (Compustat) firms. The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements.

We base our empirical strategy on the theoretical literature, which implies that financing needs and firms' capital structure are both endogenous to firms' life-cycle: startups and young firms may need to take on substantial debt, but as they approach their optimal size over time their incentives to borrow and the amount borrowed relative to firm size may decline (e.g., Cooley and Quadrini (2001), Khan and Thomas (2013), Virgiliu and Xu (2014)). Conditional on size, firm leverage can thus decrease with age over time for a given firm. At the same time, conditional on age, firms that experience better shocks and grow more can afford to take on more debt with higher net worth resulting from growth. As a result, a larger size may be associated with higher ability to borrow, and hence higher leverage (e.g., Albuquerque and Hopenhayn (2004) and Gopinath, Kalemli-Ozcan, Karabarbounis and Villegas-Sanchez (2017)). The "type" of financing may also differ over the firm life-cycle. Publicly-traded firms have easier access to a variety of financing options—equity, bonds, loans, etc. Although these forms of financing may also be available for certain privately-held firms (especially, the large ones), smaller firms mainly use bank loans for their financing (see, e.g., Caglio, Darst and Kalemli-Ozcan (2024)). Using our unique longitudinal data that contains information on firm size, age, and financing structure, we can test these theoretical predictions.

We find that financial leverage is systematically related to firms' life-cycle characteristics: conditional on age, large firms are more leveraged, and conditional on size, older firms are less leveraged. This finding of conditional dependence is the prediction of many models such as Cooley and Quadrini (2001) and Albuquerque and Hopenhayn (2004). Importantly, these findings pertain specifically to privately-held firms, but not publicly-traded ones. Moreover, we find that the relationship between leverage and firm size and age holds regardless of debt maturity (i.e., short-term and long-term leverage) and across different time periods (i.e., pre- and post-Great Recession). We also find that, within firms, leverage is positively associated with employment growth, but this relationship turns negative during the post-recession period. One possible interpretation is that during the booms higher debt is associated with more borrowing that facilitates firm growth, whereas, during the busts, it acts more as a constraint that impedes growth. Thus, business cycles in the U.S. appear to be systematically related to the debt of privately-held firms.

Using the Great Recession episode as a shock to aggregate credit conditions, we employ a difference-in-differences specification to test whether firms that enter the crisis with high leverage reduce their leverage and experience lower employment growth. A strength of our strategy is satisfaction of parallel trends assumption needed for difference-in-differences identification by construction: high and low leverage firms before the crisis do not differ once we condition on the life-cycle determinants of leverage and how the differences in life-cycle variables trend before and after the crisis. Put differently, growth outcomes of high and low leverage firms differ after the crisis due to life cycle characteristics that in turn determine firms being high and low leverage at the onset of the crisis.

We find that highly-leveraged firms tend to deleverage during the crisis, but highly-leveraged small firms, and especially small-young firms, deleverage the most. We then find that deleveraging does not translate into lower employment growth for all types of firms. While highly-leveraged firms as a whole grow 5% less compared to others, this effect mainly comes from highly-leveraged small firms, which grow 11% less, and also highly-leveraged small-young firms, which grow 21% less. Our results indicate that in the presence of tighter credit conditions for the aggregate economy, high leverage acts as a constraint only for small and small-young firms and but not necessarily on large firms.

The aggregate implications of these firm-level findings point to the first-order importance of heterogeneity in financial constraints and when those constraints bind for which firms. If we ignore the interaction between leverage and firm life-cycle, we would conclude that highly-leveraged firms account for 3% of excess job loss during the Great Recession—lower than the share of total employment this group accounts for (5%) before the onset of the Great Recession. Thus, one may conclude that firm leverage is not important for firm growth. However, once we consider heterogeneity in financial constraints, we find much more disproportionate effects. Highly leveraged small firms account for 5.2% of excess job losses during the crisis, but only 3.2% of total employment. The most affected group, highly leveraged small-young firms account for 4% of excess job losses, despite accounting for only 1.3% of total employment. These effects highlight the important role of firm financial heterogeneity for understanding the aggregate effects of financial shocks.

Our results are consistent with a large literature arguing that adverse shocks are propagated to the aggregate economy via small firms' borrowing constraints (e.g., Bernanke et al. (1999) and Gertler and Gilchrist (1994)). Recent work by Crouzet and Mehrotra (2020) confirmed that small firms are more sensitive to aggregate shocks, but contrary to previous work and our paper, this excess sensitivity cannot be explained by financial constraints. Our results are consistent with both set of papers given the endogeneity of financial constraints to firms' life-cycle. Depending on where small firms are in their life-cycle, small firms' financial constraints may or may not explain their sensitivity to aggregate shocks.[2]

The rest of the paper is organized as follows. Section 1 describes the data construction, presents descriptive statistics, and addresses selection in financial reporting. Section 2 studies the relationship between firm leverage and key firm life-cycle indicators – firm age and size. Section 3 uses the Great Recession to analyze the impact of an aggregate credit shock on firm leverage and employment. Section 4 concludes.

1 Data and Descriptive Statistics

To provide a comprehensive picture of firm financing and its connection to firm and aggregate outcomes, we first construct a new database that incorporates information on firm financials, employment, and age for both privately-held and publicly-traded firms.

1.1 Publicly-Traded Firms and Aggregate Economic Activity

Much of what is known about firm financing and real outcomes for U.S. firms is based on evidence from Compustat, which only covers publicly-traded companies. In this section we evaluate the contribution of these firms to the aggregate economy.

Calculating the contribution of publicly-traded firms in Compustat to the U.S. economy is not straightforward.[3] First, not all firms in Compustat (North America) operate establishments in the United States. We identify a firm as operating in the U.S. if it satisfies one or more of the following criteria: (i) is headquartered in the U.S.; (ii) reports an Employer Identification Number (EIN), which is required for payroll tax purposes;

[2]The aforementioned papers use QFR data. Because QFR does not contain longitudinal information on firm employment and age, it cannot fully capture time-varying and endogenous nature of financial constraints with respect to the firm's own life-cycle as the longitudinal LOCUS data can.

[3]Our basic cleaning of Compustat data involves: 1) keeping one observation per (gvkey, year) pair; 2) keeping one observation per (ein, year); 3) dropping firms in the financial sector (NAICS code 52) or public administration (NAICS code 92).

(iii) lists the United States as one of its markets.[4] Second, not all firms in Compustat are actively traded. Following Davis, Haltiwanger, Jarmin and Miranda (2006), we define active publicly-traded firms as those with a positive security price in a particular year or in the years that bracket that year.

Between 2005 and 2012, around 5,080 non-financial firms were actively publicly-traded annually at any point in time, accounting for roughly 0.1% of all firms in the economy.[5] Less clear is the fraction of employment and revenue these firms account for.

Determining the fraction of employment and revenue of publicly-traded firms is especially challenging. As noted in Davis et al. (2006), while the LBD measures the total number of employees that are subject to U.S. payroll taxes and total domestic revenue, Compustat measures the total number of employees and revenue of domestic and foreign subsidiaries. These differences give rise to discrepancies between the LBD and Compustat reported employment and revenue. Similar to Davis et al. (2006), we compare the LBD and Compustat employment and revenue of matched publicly-traded firms.[6] Between 2005 and 2012, LBD employment is, on average, 71% of Compustat employment and LBD revenue is, on average, 81% of Compustat revenue. It is therefore important to adjust Compustat reported employment and revenue when calculating the contribution of publicly-traded firms to the U.S. economy because official aggregate statistics measure domestic employment and domestic gross output.

To highlight the importance of taking into consideration (i) whether firms operate domestically, (ii) are actively traded, and (iii) the domestic portion of employment and revenue, we report three estimates of publicly-traded firms' contribution to the U.S. economy. The "raw" contribution of publicly-traded firms is measured as the sum of Compustat employment (*emp*) and revenue (*revt*) across all publicly-traded firms that (likely)

[4]We identify the United States as a market if one of two criteria are met: (i) the Compustat Segments data lists "USA" as a market; (ii) the business description in Compustat includes the *word* "United States", "USA", or "US".

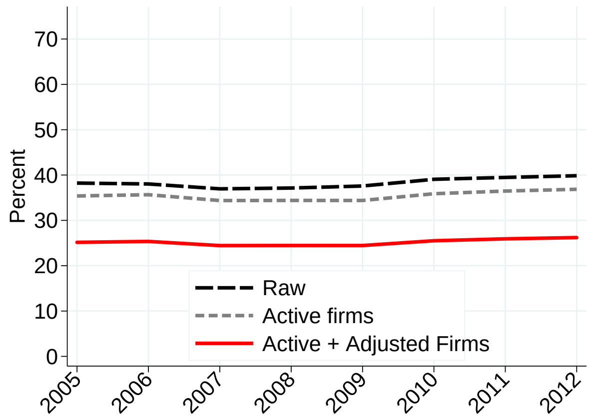
[5]The 5,080 figure is arrived at by implementing basic Compustat cleaning, and focusing on actively publicly-traded firms with (likely) domestic operations. The 0.1% figure is arrived at by dividing 5,080 by 4,982,403, which is the average number of non-financial firms in the U.S. economy between 2005 and 2012 derived from the Census Bureau's Business Dynamic Statistics data. See Appendix A for additional details.

[6]Our employment share is consistent with this earlier work by Davis et al. (2006), who only looked at the employment share, where we also calculate the aggregate gross output share. Zetlin-Jones and Shourideh (2017) document similar numbers both for employment and output shares for the United Kingdom.

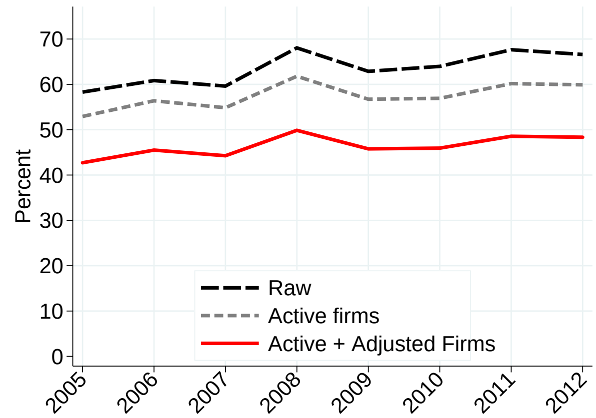
operate in the United States, divided by total BDS employment and BEA gross output.[7] We then report the contribution of "active" firms by summing Compustat reported employment and revenue across all actively publicly-traded firms that operate domestically and dividing them by total BDS employment and BEA gross output, respectively. Finally, we report the ("active & adjusted") version that approximates domestic employment and revenue by adjusting the Compustat totals (by a factor 0.7109 for employment and by a factor 0.8070 for output) across all actively publicly-traded firms that operate domestically and dividing them by total BDS employment and BEA gross output, respectively. Appendix A fully details how the contribution of publicly-traded firms is calculated, and provides several alternative estimates based on different approaches to identifying publicly-traded firms that operate within the United States.

Figure 2 reports the contribution of publicly-traded firms to total employment and revenue. First, note that in both figures, the contribution has remained quite stable over the entire period 2005-2012. In the left panel, Compustat firms (that operate domestically) account for, on average, around 38% of non-financial private sector employment when no adjustments are made for active trading and foreign employment. This average falls to 35% if only actively-traded firms are considered, and falls further still to 25% when the domestic employment of actively traded firms is considered. The right panel repeats the exercise for revenue. Similar to the employment contribution, the contribution of publicly-traded firms is fairly stable over time. Compustat firms account for around 64% of private sector gross output on average when no adjustments are made for active trading and foreign employment. This average falls to 58% if only actively-traded firms are considered and falls further still to 46% when the domestic gross output of actively traded firms is considered. These figures indicate that privately-held firms account for the majority of employment (nearly 75%) and gross output (nearly 54%). Therefore, to understand aggregate fluctuations, especially in employment, it is important to study privately-held firms.

[7] Total U.S. employment is obtained from the Census Bureau's Business Dynamic Statistics (BDS). Total gross output is obtained from the Bureau of Economic Analysis' Industry Economic Accounts. Gross output measures revenue, including both final users and other industries. Our measures exclude employment and output of firms in the financial sector (NAICS code 52) or public administration (NAICS code 92).



(a) Employment



(b) Revenue

Figure 2: Compustat Firms Share of Employment and Revenue

Notes: The figures depict the contribution of publicly-traded firms to non-financial private sector (a) employment and (b) revenue (after dropping financial and government sectors). Publicly-traded firm employment and revenue are obtained from Compustat. Private sector employment is obtained from the Census Bureau's BDS tables and revenue from the BEA's Industry Economic Accounts tables. In each figure the "raw" line depicts the raw Compustat value for listed firms that operate domestically over the private sector value; the "active firms" line depicts the raw Compustat value for actively publicly-traded firms that operate domestically over the private sector value; and the "active + adjusted firms" line depicts the adjusted (by a factor of 0.7109 for employment and 0.807 for revenue) Compustat value for actively publicly-traded firms that operate domestically over the private sector value.

1.2 Existing Datasets for Privately-Held Firm Financing

Research on the financing behavior of privately-held firms has relied mainly on two types of data. The first type, including SDC VentureXpert and CapitalIQ, focuses on private equity issuance and buyouts. As a result, these data provide no information on bank debt or bonds on balance sheets, and only include the very small sample of firms that raise private equity.[8] The second type focuses on very small and young businesses. The Survey of Small Business Finance (SSBF) is a cross-sectional survey conducted in four waves between 1987 and 2003 by the U.S. Federal Reserve. The 2003 survey, for instance, sampled under 5,000 firms from a target population of non-financial firms with less than 500 employees. There is also loan-level data from the Small Business Administration

[8] Bernstein, Giroud and Townsend (2016) uses VentureXpert to analyze how monitoring by venture capitalists affects the innovation and growth of 23,000 venture-backed companies between 1977 and 2006. Davis, Haltiwanger, Handley, Jarmin, Lerner and Miranda (2014) use CapitalIQ to track changes in jobs and productivity among a sample of 3,200 firms targeted for leveraged buyouts between 1980 and 2005.

(SBA), which only provides info on loans.[9]

Similarly, the Kauffman Firm Survey (KFS) focuses on very young firms. It tracks a single cohort of about 5,000 firms born in 2004 through 2011.[10] These data cover a highly select set of privately-held firms that are not representative of the U.S. economy in general, and none of them covers the entire balance sheet to learn about different forms of financing over the firm life-cycle.

Two exceptions that cover a larger set of privately-held firms are Sageworks and the U.S. Census Bureau's Quarterly Financial Report (QFR). Sageworks, which is a proprietary dataset, contains panel data for over 220,000 publicly-traded and privately-held firms. Similar to Moody's Orbis, Sageworks includes information on firm balance sheets and income statements, as well as industry classification and geographic location. In contrast to Orbis, Sageworks anonymizes firms (Asker, Farre-Mensa and Ljungqvist, 2015). This feature prevents matching it to other sources, such as the LBD, that contain information on age and employment. Due to the inability to match the Sageworks to Census micro data, it is not possible to assess its representativeness.

Finally, QFR covers the mining, manufacturing, wholesale, retail, and select service sectors. Each quarter, it surveys about 4,600 large corporations in these sectors, along with a select sample of about 5,000 small and medium sized firms in the manufacturing sector. In the literature using QFR, the focus typically is on manufacturing firms because QFR is more representative of this sector.[11] QFR contains detailed balance sheet information for several thousand privately-held and publicly-traded firms across the age and size distributions in the manufacturing sector. Two features distinguish LOCUS from the QFR. First, LOCUS encompasses a large sample of small and large firms outside the manufacturing sector, which is critical because the manufacturing sector only accounts for roughly 10% of U.S. employment in recent years. Second, and more importantly, because QFR can only be linked to the LBD in Economic Census years, it does not contain longitu-

[9] The SSBF has been used to study borrower-lender relationships as in Petersen and Rajan (2002).

[10] Robb and Robinson (2012) use the survey to document the importance of bank financing for startups.

[11] Firms that have total assets below industry-specific cutoffs are selected to be part of the survey by stratified random sampling, where the strata are defined by industry and asset size. These sampled firms remain in the QFR for eight consecutive quarters and then subsequently cannot be sampled for a certain period of time, which is also determined by its size (based on total assets). Firm that have total assets above the industry-specific cutoffs are sampled with certainty in each quarter.

dinal information on key firm life-cycle characteristics, including firm employment and age. Given the endogeneity of financial constraints to firm life-cycle, this is an important shortcoming of QFR for the questions we ask in this paper.

1.3 LOCUS Data: Matching LBD, Orbis, and Compustat

LOCUS matches the LBD to Moody's Orbis and Compustat. The LBD has comprehensive data on firm age, employment, industry, and legal form for nearly the universe of privately-held firms, but lacks information on firm balance sheets. Compustat contains comprehensive and widely used financial data for publicly-traded firms. For a large sample of privately-held U.S. firms, Orbis contains similarly detailed financial data from firm balance sheets, income statements, and profit and loss accounts. Orbis is compiled by Moody's Bureau van Dijk Electronic Publishing (BvD). Firm-level data are relayed to BvD through 40 different information providers such as local chambers of commerce.

We match LBD to Compustat and Orbis using both firm-level identifiers (EINs) and an iterative probabilistic name and address matching procedure (see Appendix B.1 for more details). Using our procedure, we match around 81% of target Compustat observations and firms, and 77% of target Orbis observations and 69% of Orbis firms. For Compustat, three-fourths of the matches are based on EIN and one-fourth are based on probabilistic name and address matching. For Orbis, 78% of the matches are based on EIN, and the remainder on name and address matching (see Appendix B.2 for more details). To construct the data used for analysis, we clean the financial data for the matched sample for basic reporting mistakes and verify the internal consistency of balance sheet data (see Appendix B.4 for more details).

The resulting LOCUS dataset contains around 166,400 unique firms, 96% of which are privately-held. Our matched sample covers around 26% of employment, 31% of payroll, and 43% of private sector, non-financial revenue. Orbis data thus does not cover all privately-held firms. The Compustat match is also less than 100% as typical in this literature.[12] Overall, Compustat matched sample accounts for 20% of total employment and

[12] See Tello-Trillo and Streiff (2020) for details on the LBD-Compustat bridge produced by the Center for Economic Studies at U.S. Census Bureau. The match rate for their bridge is 85%.

36% of total revenue of publicly-traded firms.[13]

Table 1 details what we have shown in Figure 1 for employment and also shows revenue distribution. Publicly-traded and privately-held firms are vastly different in terms of size, measured by employment or revenue. The median publicly-traded firm is nearly 24 (67) times the size of the median privately-held firm in terms of employment (revenue). Incorporating information on privately-held firms is critical for better capturing the U.S. firm size distribution. In doing so, LOCUS substantially improves the coverage of small and medium sized firms both in terms of employment and revenue, relative to the sample of publicly-traded firms.

Table 1: LBD and LOCUS Employment and Revenue Pseudo-Percentiles

		(1) 10th	(2) 25th	(3) 50th	(4) 75th	(5) 90th
Employment	Employer businesses (LBD)	1	2	4	9	25
	Privately-held LOCUS	4	10	26	71	203
	Publicly-traded LOCUS	22	111	611	3,274	12,420
Revenue ($M)	Employer businesses (LBD)	0.09	0.19	0.47	1.28	3.78
	Privately-held LOCUS	0.32	1.11	3.86	11.69	33.54
	Publicly-traded LOCUS	7.05	45.22	259.3	1,160	4,333

Notes: Reports the 10th, 25th, 50th, 75th, and 90th pseudo-percentiles of firm employment and real revenue (USD, constant 2012 millions) among all employer businesses from the LBD, privately-held LOCUS firms, and publicly-traded LOCUS firms between 2005 and 2012. Pseudo-percentiles are calculated to be in compliance with U.S. Census disclosure requirements.

1.4 LOCUS Data: Accounting for Selection

Although LOCUS resembles the LBD firm size distribution more closely than Compustat alone, Figure 1 and Table 1 illustrate that privately-held firms in LOCUS are not necessarily representative of the U.S. economy. The average employment of privately-held firms in LOCUS is 147 versus just 24 in the LBD; and the average age is 22 in LOCUS versus 13 in the LBD. Additionally, LOCUS firms tend to have higher employment growth rates, are more likely to own multiple establishments, and are more likely to be nonprofits than firms in the LBD.

[13] After taking into account that we match 81% of Compustat firms, we confirm our previous estimates that publicly-traded firms would account for 25% ($100 \times 0.2/0.81$) of total U.S. employment and 45% ($100 \times 0.362/0.81$) of total U.S. revenue. These numbers line up closely with the estimates that we report based on a different approach in Section 1.1.

This selection is driven by the fact that our sample contains only privately-held firms that chose to voluntarily report their financials (Orbis). The selection patterns are a concern because firm financing decisions are likely influenced by factors such as age, size, and growth. Analysis based on the raw LOCUS data will therefore likely misrepresent the relationship between leverage and firm characteristics because the average firm in our raw data is older, larger, and grows faster than the average firm in the U.S. economy.

We are able to address this selection head-on because we matched Orbis with the LBD, which covers nearly all employer firms in the United States. We implement a series of logistic regressions similar to Haltiwanger, Jarmin, Kulick and Miranda (2017) for privately-held firms.[14] Our dependent variable (R_{it}) is an indicator for the reporting of financial information in Orbis by firm i in year t, and is thus equal to one for the firm-year observations in the privately-held sub-sample of LOCUS, and zero otherwise. To account for the possibility that selection into our matched data varies over time, we estimate separate models for each year, 2005 through 2012. To further account for the possibility that selection varies for firms continuing, entering and exiting as employer-businesses, we estimate separate models for each of these categories.[15] Our explanatory variables are firm employment ($log(emp_{it})$), age (age_{it}), an indicator for firms 16 years or older ($D16_i$), employment growth rate (EG_i, 7 categories), and a series of fixed effects for 2-digit NAICS industry (ind_i), multi-unit status (mu_{it}), and legal form (lfo_{it}, 3 categories).[16] The models we estimate are:

1. **Continuers:**

$$R_{it} = \alpha + \gamma_1 log(emp_{it}) + \gamma_2 age_{it} + D16_i + EG_{it} + ind_i + mu_{it} + lfo_{it} + \varepsilon_{it} \qquad (1)$$

[14] We exclude publicly-traded firms from the logistic regressions and assign them a weight of one in our subsequent analysis because they are required to report financials.

[15] Note that the three categories are determined by looking at a firm's employment status in $t-1$ and t. A continue is defined as a firm that has positive employment in both $t-1$ and t. An entrant is a firm that only has positive employment in t; and an exiter is a firm that only has positive employment in $t-1$. Throughout its life-cycle, a firm can have multiple spells in which it is an entrant, exiter, and continuer.

[16] Legal form is divided into three categories – 1) C corporations, 2) sole-proprietors, partnerships, and S corporations, and 3) non-profits and other legal forms.

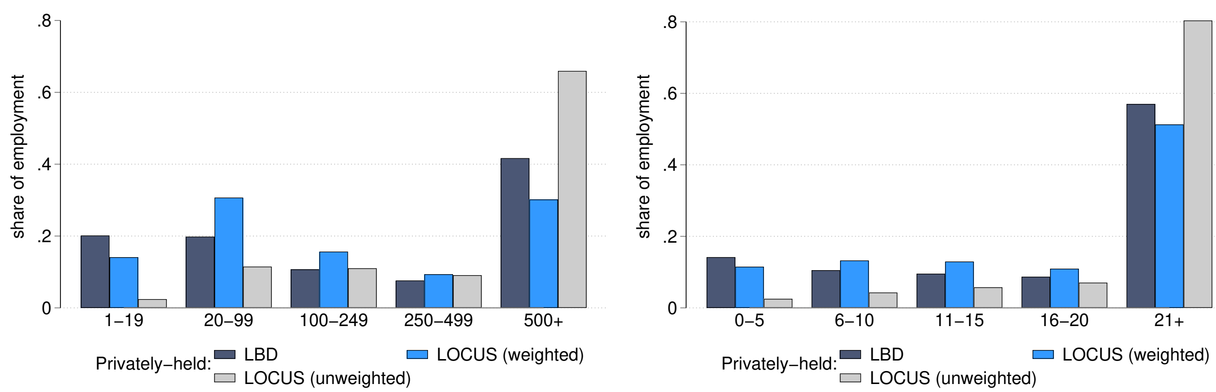
2. **Entrants:**

$$R_{it} = \alpha + \gamma_1 log(emp_{it}) + \gamma_2 age_{it} + D16_i + ind_i + mu_{it} + lfo_{it} + \varepsilon_{it} \tag{2}$$

3. **Exiters:**

$$R_{it} = \alpha + \gamma_1 log(emp_{it}) + \gamma_2 age_{it} + D16_i + ind_i + mu_{it} + lfo_{it} + \varepsilon_{it} \tag{3}$$

The resulting predicted values are used to construct propensity scores, which serve as weights in the remainder of the analysis. As Figure 3 below, and Figure C.1 and Tables C.1 and C.2 in Appendix C show, applying weights substantially decreases the observable differences between firms reporting financials and firms who do not report.[17] In particular, the weights mitigate the over-representation of old, large, and multi-unit firms in the unweighted LOCUS data. The approach also addresses the over-representation of non-profit firms, which likely make different financing decisions than sole-proprietors, partnerships, and corporations.



(a) Firm Size (Employment)

(b) Firm Age

Figure 3: Distribution Comparisons (% of emp)

Notes: Theses figures compares the fraction of sample firm-level employment accounted for by each size (L) and age (R) group. Each bar represents a different sample. The first bar represents all private, non-financial employer businesses in the LBD. The second bar represents the weighted LOCUS sample of privately-held firms, where the weights are derived from estimating equations (3) through (5). The third bar represents the unweighted LOCUS sample of privately-held firms, where each firm gets equal weight.

[17] In the figures the height of each bar, and in the tables the share reported, is the share of sample employment accounted for by each group.

1.5 LOCUS Data: Distribution Comparisons

All of the analysis in the remainder of the paper uses the weights constructed to account for selection. It is therefore worth further highlighting how propensity score weighting helps make the LOCUS data more representative. We do so briefly by comparing the distribution of key variables of interest across three data sources: LOCUS, LBD, QFR. Our motivation for using QFR for comparison is twofold: first, as mentioned earlier, the data cover a large set for privately-held firms; and second, it has been used in the literature to study the financing behavior of firms (Gertler and Gilchrist, 1994; Kudlyak and Sanchez, 2017; Crouzet and Mehrotra, 2020).

Specifically, we compare the distributions of total assets, revenue, firm age, and employment across LOCUS, QFR, and LBD. Total assets is only available for LOCUS and QFR, and we obtain the data from each source respectively.[18] Firm revenue, age, and employment is available in the LBD, and we therefore use it as the source for these variables. In order to do so, we restrict our comparison to 2007, which is the only Economic Census year in our sample period. We do so because the QFR can only be linked to the LBD in Economic Census years. The QFR is reported at the EIN level, and we use these EINs to link observations in QFR to the LBD. Similar to LOCUS, the QFR does report sampling weights, which we use for calculating the pseudo-percentiles reported below.[19]

[18] To be consistent with LOCUS, in which we have annual firm balance sheets, we only consider firms in QFR that report total assets in Q4 when we report psuedo-percentiles for total assets.

[19] In some cases, the QFR samples multiple EINs that, when linked to the LBD, appear to belong to the same firm. Because we use LOCUS and LBD at the firm level, in cases where multiple EINs match to the same firm, we keep only one observation per firm and we use the sampling weight that corresponds to the EIN with the largest employment in LBD.

Table 2: Psuedo-Percentiles: Mfg. Firms in QFR, LOCUS and LBD

Variable	Source	(1) 10th	(2) 25th	(3) 50th	(4) 75th	(5) 90th
Total Assets ($M)	QFR	0.231	0.440	1.174	3.543	12.14
	LOCUS	0.251	0.591	1.418	3.347	7.921
Revenue ($M)	QFR	0.677	1.210	2.669	6.874	18.20
	LOCUS	0.596	1.281	2.924	6.555	13.02
	LBD	0.144	0.331	0.961	3.297	10.92
Age	QFR	6	12	21	31	31
	LOCUS	2	7	16	28	31
	LBD	1	6	14	26	31
Employment	QFR	5	9	18	40	91
	LOCUS	2	7	16	31	58
	LBD	1	3	8	22	61

Notes: Reports the 10th, 25th, 50th, 75th, and 90th pseudo-percentiles of total assets ($, constant 2012 millions), revenue ($, constant 2012 millions), firm age, and employment among manufacturing firms (NAICS sectors 31-33) in QFR, LOCUS, and LBD in 2007. Pseudo-percentiles are calculated to be in compliance with U.S. Census disclosure requirements.

In Table 2, we take into account that QFR primarily covers the manufacturing sector, and compare the distributions of total assets, revenue, firm age, and employment of manufacturing firms in QFR, LOCUS, and LBD. Two patterns are apparent. First, the QFR and LOCUS distributions for total assets and revenue are similar, though the bottom half of the distribution (10th, 25th, and 50th percentiles) of QFR is slightly smaller than LOCUS. This is comforting because QFR is explicitly stratified on industry, total assets, and receipts, the latter of which is distinct from but related to revenue, while LOCUS weights are based on a distinct set of variables (industry, employment, age, employment growth, multi-unit status, and legal form). Second, on firm age and employment, two variables that are the focus of this paper and are not used to stratify QFR, the distribution of LOCUS is closer than QFR is to the LBD.

Table 3: Pseudo-Percentiles: Mfg. in QFR and All in LOCUS and LBD

Variable	Source	(1) 10th	(2) 25th	(3) 50th	(4) 75th	(5) 90th
Total Assets ($M)	QFR	0.231	0.439	1.174	3.543	12.14
	LOCUS	0.153	0.419	1.118	3.217	10.31
Revenue ($M)	QFR	0.677	1.210	2.669	6.874	18.20
	LOCUS	0.318	0.860	2.208	5.402	12.13
	LBD	0.093	0.120	0.489	1.331	3.915
Age	QFR	6	12	21	31	31
	LOCUS	1	4	10	21	31
	LBD	1	3	9	19	30
Employment	QFR	5	9	18	40	91
	LOCUS	1	3	9	21	48
	LBD	1	2	4	10	25

Notes: Reports the 10th, 25th, 50th, 75th, and 90th pseudo-percentiles of total assets ($, constant 2012 millions), revenue ($, constant 2012 millions), firm age, and employment among manufacturing firms (NAICS sectors 31-33) in LOCUS, QFR, and LBD in 2007. Pseudo-percentiles are calculated to be in compliance with U.S. Census disclosure requirements.

In Table 3, we take advantage of the fact that LOCUS includes firms outside of manufacturing, and compare the distributions of manufacturing firms in QFR to all firms in LOCUS and LBD. Two patterns in the data are worth noting. First, across all percentiles of total assets, revenue, firm age, and employment firms in the whole economy (LBD and LOCUS) are smaller than those in the manufacturing sector (QFR). Second, after adjusting for selection, the distribution of LOCUS is quite similar to that of LBD across all variables.

Ultimately, this exercise highlights the value of LOCUS data. The data includes a larger number of firms (particularly privately-held ones) over time relative to other datasets available in the U.S.: it covers firms outside of manufacturing, has both firm financial and life-cycle characteristics, and becomes representative of the U.S. economy after addressing selection.

2 Firm Financing over the Life-Cycle

By using data on a representative set of U.S. firms, we start by testing two key predictions of existing firm dynamics models with financial frictions: conditional on age, larger firms borrow more and conditional on size, younger firms borrow more. We report results separately for privately-held and publicly-traded firms to be able to compare our results on publicly-traded firms to the existing literature.

2.1 Econometric Specification and Descriptive Statistics

To better understand the relationship between firm's life-cycle characteristics (size and age) and firm financing, we regress our measure of financial frictions, firm leverage, on life-cycle variables, firm age and size and other possible determinants of firm leverage in the full pooled sample of firms, as well as separately for publicly-traded and privately-held firms:

$$\begin{aligned} LEV_{it} =& \alpha + (\omega_s \times \lambda_t) + (\gamma_c \times \lambda_t) + \beta_1 \log(EMP_{it}) + \beta_2 AGE_{it} + \beta_3 COLLAT_{it} + \\ & \beta_4 PROFIT_{it} + \beta_5 RG_{it} + \epsilon_{it} \end{aligned} \tag{4}$$

where i is the firm and t is time, measured in years. $(\omega_s \times \lambda_t)$ are industry×year fixed effects, where industry is the 4-digit NAICS level and $(\gamma_c \times \lambda_t)$ are county×year fixed effects. These fixed effects account for any time varying industry and geography-specific effects. Notice that this regression relies on between-firm variation since we do not include firm fixed effects.

The above regression is a standard firm leverage regression in the finance literature. We control for firm collateral ($COLLAT_{it}$), measured as tangible fixed assets over total assets, and profitability ($PROFIT_{it}$), measured as the ratio of net income to total assets.[20] The literature also uses Tobin's Q as a measure of growth potential. Because 96% of our sample is composed of privately-held firms, we do not use a Tobin's Q measure. In-

[20]Profits-to-total assets is the standard measure of profitability, but the ORBIS data contains many missing records for profits. Net income over total assets is used instead and for the subsample for which both profits and net income are available, we verify that there is a high correlation between profits over total assets and net income over total assets.

stead, we use revenue growth (RG_{it}) to control for growth potential. To this standard regression, we add employment $(log(EMP_{it}))$ and age (AGE_{it}) as regressors to capture life-cycle stages of firms. The corporate finance literature also controls for size, mainly by using assets. Given the valuation effects, employment is a more appropriate measure of size because the book value of assets will not reflect true size. In constructing our analysis data, we winsorize all financial variables—all the leverage variables, collateral and profitability—at the 1st and 99th percentiles.

Table 4 summarizes the key variables of interest for publicly-traded and privately-held firms in LOCUS. The table highlights that publicly-traded and privately-held firms are at starkly different points in their life-cycle. Publicly-traded firms have 227 times the size (employment-based) of privately-held ones and are 1.4 times as old. Additionally, publicly-traded firms have higher collateral and financial leverage. When we decompose leverage into short-term and long-term, privately-held firms have higher short-term leverage, while publicly-traded firms have higher long-term leverage. Moreover, privately-held firms have higher growth compared to publicly-traded firms.

Table 4: Summary Statistics: LOCUS (weighted) Data

	Public		Private (weighted)	
	(1)	(2)	(3)	(4)
	mean	SD	mean	SD
financial leverage	0.21	0.25	0.17	0.25
short-term leverage	0.03	0.08	0.05	0.12
long-term leverage	0.18	0.23	0.13	0.22
log(EMP)	6.61	2.34	2.40	1.33
AGE	23.04	9.92	15.99	11.03
$COLLAT$	0.23	0.23	0.17	0.24
$PROFIT$	-0.06	0.30	0.16	0.40
RG	0.07	0.41	0.12	0.48

Notes: This table compares the mean and standard deviation of key variables for privately-held and publicly-traded firms. The means and standard deviations are weighted, where the weights are derived from estimating equations (3) through (5). Financial leverage short-term plus long-term debt over total assets. Short-term leverage is short-term debt over total assets. Long-term leverage is long-term debt over total assets. log(EMP) measures log(firm-level total employment). AGE measures the firm age. $COLLAT$ is measured as tangible fixed assets over total assets. $PROFIT$ is net income over total assets. RG is measured as the DHS growth rate in revenue between $t-1$ and t.

2.2 Leverage and Life-Cycle: Baseline Results

In Table 5, we focus on the relationship between financial leverage, measured as short-term plus long-term debt over total assets, and firm life-cycle characteristics. Consistent with the previous literature, regardless of firm type, there is a positive relationship between firm size and collateral, and leverage and a negative one between profitability and financial leverage. That is, larger firms and higher net worth firms are more leveraged and more profitable firms are less leveraged. A one standard deviation increase in size is associated with a 16% increase in financial leverage for privately-held firms and a nearly 20% increase in financial leverage for publicly-traded firms.

The new result is on firm age: there is a negative relationship between firm age and leverage, but only for privately-held firms, which seem to drive the result in the "all" firms sample. There is no relationship between age and leverage for publicly-traded firms. A one standard deviation increase in firm age is associated with 17% lower financial leverage for privately-held firms.[21]

While the focus on financial leverage in Table 5 is broadly consistent with the empirical literature (e.g., Rajan and Zingales (1995), Anderson and Cesa-Bianchi (forthcoming)), generally the macroeconomic models that incorporate financial frictions model these as short term debt (e.g., Cooley and Quadrini (2001), Gopinath et al. (2017)). Therefore, in Table 6, we explore whether the relationship between leverage and firm characteristics for privately-held and publicly-traded firms differs depending on whether we consider short-term leverage or long-term leverage.

Examining short versus long-term maturity does not lead to substantially different results for privately-held firms; the relationship between size and leverage is still positive, and age and leverage is negative, both when we look at short-term and long-term leverage. Interestingly, the marginal effect of size is stronger for short-term leverage than long term leverage. A one standard deviation increase in size is associated with a 31% increase in short-term leverage and a 13% increase in long-term leverage. Meanwhile,

[21]In Appendix D, Tables D.1 and D.2 show that these findings are robust to changing the fixed effects (year FE and industry-year FE) and considering different controls (measuring size by total assets and including cash over total assets as an additional control).

Table 5: Financial Leverage Regressions (2005-2012)

	(1) all	(2) private	(3) public
log(EMP_{it})	0.0209	0.0212	0.0177
	(0.00249)	(0.00256)	(0.0029)
AGE_{it}	–0.00265	–0.00266	0.000182
	(0.000267)	(0.000267)	(0.000504)
$COLLAT_{it}$	0.215	0.215	0.214
	(0.0181)	(0.0182)	(0.0364)
$PROFIT_{it}$	–0.0670	–0.0670	–0.200
	(0.00612)	(0.00612)	(0.016)
RG_{it}	0.0044	0.00442	–0.0112
	(0.00326)	(0.00326)	(0.00536)
county x yr FE	Y	Y	Y
4-digit x yr FE	Y	Y	Y
weighted	Y	Y	NA
observations	357500	338000	19500
firm count	142300	138000	4300
r-squared	0.2667	0.265	0.2012
ME log(size)	0.1626	0.1638	0.1983
ME firm age	–0.1699	–0.1702	0.0086

Notes: The dependent variable is financial debt/total assets. The main regressors are log(EMP_{it}) (firm size); AGE_{it} (firm age); $COLLAT_{it}$ (tangible fixed assets over total assets); $PROFIT_{it}$ (net income over total assets); and RG_{it} (DHS revenue growth). All regressions include 4-digit industry-year fixed effects and county-year fixed effects. The years are 2005–2012. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the industry and year level.

the marginal effect of firm age is stronger in the case of long-term leverage compared to short-term leverage. Specifically, a one standard deviation increase in age is associated with 12% lower short-term leverage and 19% lower long-term leverage.

For publicly-traded firms, the positive relationship between financial leverage and size noted in Table 5 is driven entirely by long-term leverage – the relationship between short-term leverage and size is negative. A one standard deviation increase in size is associated with a 17% decrease in short-term leverage, but a 26% increase in long-term leverage.[22] These results suggest that as publicly-traded firms grow larger, they opt for longer-term debt.

Taken together, the results thus far are notable for two reasons. First, if we focused only on the publicly-traded firms and the negative coefficient for size in the short-term leverage analysis, we might conclude that our results contradict many firm dynamics models with firm heterogeneity and financial frictions, which predict that smaller firms

[22]In Appendix D, Tables D.3 and D.4 show that these findings are robust to changing the fixed effects (year FE and industry-year FE), and for short-term leverage also considering different controls (measuring size by total assets and including cash over total assets as an additional control).

have lower short-term leverage. But privately-held firms tell a different story. The positive correlation between short-term leverage and size supports models featuring decreasing returns to scale and models with explicit heterogeneity in borrowing constraints as a function of size.

Second, if we focused only on publicly-traded firms, we would reject the hypothesis that firm age is associated with leverage. Here again, the evidence from privately-held firms is crucial. Privately-held firms have higher leverage when they are young. This is supported by the fact that the negative relationship between leverage and firm age is particularly strong for long-term leverage. This pattern is consistent with financial frictions models, which predict that firms pay down long-term debt as they age—particularly since many firms may need to borrow to start up.

Table 6: Short-term & Long-term Leverage Regressions (2005-2012)

	Short-term Leverage			Long-term Leverage		
	(1) all	(2) private	(3) public	(4) all	(5) private	(6) public
$\log(EMP_{it})$	0.0106	0.0109	–0.00189	0.0131	0.0131	0.0198
	(0.00102)	(0.00105)	(0.000568)	(0.00209)	(0.00214)	(0.00269)
AGE_{it}	–0.000503	–0.000506	–0.0000388	–0.00226	–0.00226	0.000246
	(0.0000615)	(0.0000615)	(0.00011)	(0.000249)	(0.000249)	(0.000448)
$COLLAT_{it}$	–0.0385	–0.0381	0.0373	0.231	0.231	0.172
	(0.0068)	(0.00676)	(0.00845)	(0.0193)	(0.0193)	(0.0327)
$PROFIT_{it}$	–0.0249	–0.0250	–0.0691	–0.0404	–0.0404	–0.128
	(0.00289)	(0.00289)	(0.00687)	(0.00569)	(0.00569)	(0.00943)
RG_{it}	–0.0000879	–0.0000624	–0.00463	0.00582	0.00581	–0.00493
	(0.00197)	(0.00197)	(0.00184)	(0.00223)	(0.00223)	(0.0054)
county x yr FE	Y	Y	Y	Y	Y	Y
4-digit x yr FE	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA
observations	357500	338000	19500	332500	313000	19500
firm count	142300	138000	4300	137300	133000	4300
r-squared	0.1829	0.1813	0.0795	0.2921	0.2903	0.1964
ME log(size)	0.3041	0.3112	–0.1678	0.1312	0.1306	0.2566
ME firm age	–0.1194	–0.1199	–0.0146	–0.1877	–0.188	0.0135

Notes: The dependent variables are short-term debt/total assets and long-term debt/total assets. The main regressors are $\log(EMP_{it})$ (firm size); AGE_{it} (firm age); $COLLAT_{it}$ (tangible fixed assets over total assets); $PROFIT_{it}$ (net income over total assets); and RG_{it} (DHS revenue growth). All regressions include 4-digit industry-year fixed effects and county-year fixed effects. The years are 2005–2012. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the industry and year level. s

2.3 Pre- and Post- Financial Crisis Results

Because our data spans the period before and during the Great Recession, we can test whether the relationships we uncovered between leverage and firm characteristics is the same in the pre-crisis (2005–2008) and post-crisis (2009–2012) periods. It is important to understand whether the cross-sectional relationships that apply during non-recessionary periods change when credit supply tightens substantially. Consider the case of firm size, for instance. Suppose that borrowing constraint is given by $k \leq bf(s)$, where $b > 0$ and $f(s)$ is an increasing function such that $f(s)/s$ is also increasing in size – consistent with the finding that leverage increases with size. If the tightening of credit is represented by a new constant $c < b$, the leverage-size profile can indicate a slower increase in leverage with size under the tighter credit environment, as $cf(s)/s$ increases at a lower rate with s compared to $bf(s)/s$.

Table 7 shows that the signs of the relationships between short-term leverage and firm size and age are broadly similar in the pre- and post-Great Recession periods for both privately-held and publicly-traded firms. This is especially true for privately-held firms. The positive relationship between short-term leverage and firm size and negative relationship with firm age remains. However, the marginal effect of size is slightly smaller in the post-crisis period, while the marginal effect of firm age is slightly stronger. For publicly-trraded firms, the relationship between short-term leverage and firm age is insignificant in both periods, and for firm size is consistently negative, but only significant in the post-crisis period.[23]

Overall, the marginal effects associated with firms size and age in Table 7 indicate that for privately-held firms the relationship between short-term leverage and firm size becomes more muted in the post-period, as leverage rises less with one standard deviation increase in size. The relationship between short-term leverage and age becomes more pronounced, as leverage declines more with one standard deviation increase in age in the post-period. The flatter size-leverage profile in the post-period is consistent with financial

[23] In Appendix D, Tables D.5 and D.6 show that these findings are robust to changing the fixed effects (year FE and industry-year FE), and for short-term leverage also considering different controls (measuring size by total assets and including cash over total assets as an additional control).

constraints becoming tighter in the post-period.

Motivated by two key findings in this section—that (1) there is a systematic relationship between leverage and firm life-cycle characteristics (size and age), and that (2) these cross-sectional relationships become stronger in the post-period in a quantitative sense for some life-cycle characteristics, we investigate whether firm leverage is a sufficient statistic for gauging the extent of the tightening of firms' financial constraints, and if so for which types of firms, following a negative aggregate credit shock.

Table 7: Short-term Leverage: Pre- and Post-Great Recession

	Pre (2005-2008)			Post (2009-2012)		
	(1) all	(2) private	(3) public	(4) all	(5) private	(6) public
log(EMP_{it})	0.0114	0.0118	–0.00191	0.00909	0.00939	–0.00180
	(0.00103)	(0.00106)	(0.000964)	(0.00183)	(0.00187)	(0.000415)
AGE_{it}	–0.000527	–0.000529	–0.0000636	–0.000485	–0.000487	–0.0000207
	(0.0000639)	(0.0000641)	(0.000149)	(0.000109)	(0.000109)	(0.00012)
$COLLAT_{it}$	–0.0456	–0.0451	0.0439	–0.0259	–0.0256	0.0299
	(0.00797)	(0.00797)	(0.00914)	(0.00737)	(0.00729)	(0.0109)
$PROFIT_{it}$	–0.0260	–0.0261	–0.0614	–0.0227	–0.0227	–0.0799
	(0.00294)	(0.00294)	(0.00445)	(0.00667)	(0.00669)	(0.0127)
RG_{it}	–0.00133	–0.00128	–0.00374	0.00347	0.00346	–0.00545
	(0.00265)	(0.00265)	(0.0029)	(0.00224)	(0.00224)	(0.00268)
county x yr FE	Y	Y	Y	Y	Y	Y
4-digit x yr FE	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA
observations	179500	169000	10500	177800	169000	8800
firm count	97800	94000	3800	98400	95500	2900
r-squared	0.1676	0.1655	0.0684	0.2094	0.2082	0.0943
ME log(size)	0.305	0.3121	–0.1694	0.2899	0.2969	–0.1604
ME firm age	–0.1105	–0.111	–0.0227	–0.1282	–0.1287	–0.008

Notes: The dependent variables is short-term leverage. The main regressors are log(EMP_{it}) (firm size); AGE_{it} (firm age); $COLLAT_{it}$ (tangible fixed assets over total assets); $PROFIT_{it}$ (net income over total assets); and RG_{it} (DHS revenue growth). All regressions include 4-digit industry-year fixed effects and county-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the industry and year level.

3 An Exogenous Shock to Firm Financing

In this section, we examine the propagation of adverse shocks to firms and the aggregate economy through firms' access to credit. In their seminal work, Gertler and Gilchrist (1994) use the U.S. Census Bureau's Quarterly Financial Report (QFR) data for the manufacturing sector (accounts 10% of aggregate employment currently) to argue that adverse shocks are transmitted to the aggregate economy via small firms, which they interpret to be more credit constrained than large firms. Using the same data for a more recent time period, Kudlyak and Sanchez (2017), also for manufacturing firms, find instead that large firms respond more to adverse shocks than small firms. The work of Crouzet and Mehrotra (2020) is also based on QFR-manufacturing and confirms the earlier work of Gertler and Gilchrist (1994): small firms are more sensitive to aggregate shocks, but this excess sensitivity cannot be explained by financial constraints.

Relative to the QFR, LOCUS contains longitudinal data on firms' life-cycle characteristics, not only for manufacturing sector, but also for other sectors. Moreover, because LOCUS contains data on financing, employment, and age, for the same time period over time, we can test the extent to which the propagation of aggregate shocks to firm and aggregate outcomes via financial constraints depends on where firms are in their life-cycle. To proxy financial shocks, we focus specifically on the Great Recession episode.

It has been extensively shown that the Great Recession constitutes an economy wide contraction of credit supply (e.g., Chodorow-Reich (2014), Giroud and Mueller (2017), Siemer (2019), Duygan-Bump, Levkov and Montoriol-Garriga (2015), Greenstone, Mas and Nguyen (2020)) that can explain employment declines both at firm and at aggregate levels. Relative to this literature, our contribution is to link declines in firm-level employment to firm-level financial constraints and then use this well identified micro elasticity to link firm-level heterogeneity in financial constraints to aggregate decline in employment.

3.1 Firm Growth and Firm Leverage Dynamics

We first investigate the relationship between employment growth and leverage before and after the Great Recession. To investigate whether employment growth is associated with a change in leverage, and whether this relationship changes when aggregate credit conditions deteriorate, we estimate the following regression:

$$\begin{aligned}\Delta \log(EMP_{it}) = &\alpha + (\omega_s \times \lambda_t) + (\gamma_c \times \lambda_t) + \beta_1 \Delta STL_{it} + \beta_2 \Delta COLLAT_{it} + \\ &\beta_3 \Delta PROFIT_{it} + \beta_4 \Delta RG_{it} + \epsilon_{it}\end{aligned} \tag{5}$$

where Δ denotes a change in any variable between $t-1$ and t, hence the outcome variable is equivalent to employment growth rate of firm i. The regressions are run separately for the pre-Great Recession and post-Great Recession periods and also separately for all firms, and privately-held and publicly-traded firms.

Table 8 documents some remarkable results: leverage and firm growth is positively and significantly associated before the Great Recession but negatively afterwards (though statistically insignificant). In addition, the positive relationship during the pre-Great Recession period is driven by privately-held firms.

Table 8: Employment Growth & Short-Term Leverage: Pre- and Post-Great Recession

	Pre (2005-2008)			Post (2009-2012)		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	private	public	all	private	public
ΔSTL_{it}	0.0676	0.0486	–0.161	–0.0254	–0.0253	–0.0181
	(0.0303)	(0.0247)	(0.0952)	(0.0279)	(0.028)	(0.0704)
$\Delta COLLAT_{it}$	–0.00166	–0.00365	0.179	–0.0320	–0.0321	0.0912
	(0.0216)	(0.0197)	(0.122)	(0.0152)	(0.0153)	(0.0793)
$\Delta PROFIT_{it}$	0.0146	0.0195	–0.0949	–0.00762	–0.00765	–0.0384
	(0.0108)	(0.0106)	(0.0375)	(0.0107)	(0.0108)	(0.0249)
ΔRG_{it}	0.0286	0.0236	0.0338	0.0377	0.0378	0.00816
	(0.0105)	(0.00877)	(0.0186)	(0.00892)	(0.00895)	(0.00908)
county x yr FE	Y	Y	Y	Y	Y	Y
4-digit x yr FE	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA
observations	71700	65000	6700	112000	104000	8000
firm count	40900	38000	2900	61700	59000	2700
r-squared	0.1759	0.1524	–0.0184	0.1851	0.1819	0.0287

Notes: We consider unbalanced samples of privately-held and publicly-traded firms separately in 2005-2008 (pre-period) and 2009-2012 (post-period). The dependent variable is employment growth rate, measured as the one-year log difference in firm employment. The main regressors are changes between $t-1$ and t in short-term leverage (STL), tangible fixed assets over total assets ($COLLAT$); net income over total assets ($PROFIT$) and DHS revenue growth (RG). All regressions include 4-digit industry-year fixed effects and county-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. Standard errors are clustered at the industry and year level.

To understand why the relationship between firm growth and leverage changes before and after the Great Recession, we next investigate the process of deleveraging during an economy-wide credit shock.

3.2 Firm Deleveraging During the Great Recession

We first test whether firms entering the financial crisis with high leverage indeed deleverage. Specifically, we estimate the following regression:

$$STL_{it} = \alpha_i + (\omega_s \times \lambda_t) + (\phi_c \times \lambda_t) + \beta_1(HL_i \times POST_t) + \mathbf{\Gamma}'(\mathbf{Z_i} \times POST_t) + \epsilon_{it} \quad (6)$$

where α_i is a firm fixed effect, $(\phi_c \times \lambda_t)$ represent county-year fixed effects that absorb regional/local demand shocks, and $(\omega_s \times \lambda_t)$ represents industry-year fixed effects that absorb sectoral demand shocks. The use of firm fixed effects allows us to identify from "within" variation, rather than cross-sectional variation across firms. The $POST_t$ dummy is equal to one in 2009-2012. HL_i is a high leverage indicator that takes a value of one when short-term leverage in the pre-crisis period is 33% or higher—corresponding to the 95th percentile of the pre-crisis leverage distribution. Z_i is a vector that contains collateral ($COLLAT$), profitability ($PROFIT$), and DHS revenue growth (RG), all defined at the firm-level in the pre-crisis period. Note that all variables measured at the firm level in the pre-crisis period take the value of that variable in the first year in the period 2005-2008 that the firm appears in the LOCUS data.

In order to investigate whether firm deleveraging varies by firm size and age, we augment Equation 6 and estimate:

$$\begin{aligned} STL_{it} = & \alpha_i + (\omega_s \times \lambda_t) + (\phi_c \times \lambda_t) + \beta_1(SMALL_i \times POST_t) + \\ & \beta_2(HL_i \times POST_t) + \beta_3(HL_i \times SMALL_i \times POST_t) + \\ & \mathbf{\Gamma}'(\mathbf{Z_i} \times POST_t) + \epsilon_{it} \end{aligned} \quad (7)$$

where $SMALL_i$ is a small firm (small-and-medium-sized, SME) indicator that takes a value of one when employment in the pre-crisis (2005-2008) period is less than 500 employees. In other specifications, we further breakdown the $SMALL_i$ indicator into $SYOUNG_i$ (small-young) and $SOLD_i$ (small-old), where young is defined as firms aged ten or younger.

Table 9 shows that highly leveraged firms responded to the aggregate credit shock by deleveraging, with the effect primarily driven by the deleveraging of highly leveraged small (and highly-leveraged small-young firms). The first column shows that deleveraging of small and large firms is similar, given the insignificant interaction coefficient. In contrast, firms that entered the crisis highly leveraged experienced significant deleveraging (column 2): highly leveraged firms have 18 percentage points (p.p.) lower leverage in the post crisis period than firms that enter the crisis with less leverage.

Interestingly, column 3 shows that, among highly leveraged firms, small firms experienced significantly more deleveraging relative to large firms: leverage is 8 p.p. lower among high leverage small firms than high leverage large firms, and the total effect of high leverage for small firms during the crisis is -18 p.p., consistent with the magnitudes in column 3. Columns 2 and 3 together indicate that among highly-leveraged firms small ones deleveraged much more relative to others during post-crisis period.

Column 4 further reveals that the deleveraging effect is strongest among highly leveraged small-young firms. Specifically, the total effect of high leverage on small-young firms during the crisis is -21 percentage points. Columns 5 and 6 show that these insights are robust to alternative definitions of small and highly leveraged: the results continue to hold if the small firm (or SME) threshold is lowered from 500 employees to 100 employees, or if the high leverage threshold is lowered from 33% to 15%.[24]

Next, we investigate the impact of deleveraging on firm growth.

[24] The F-tests in the last four rows the table report whether the total effects of being highly leveraged, small, small and young, and small and old are significant. We consistently find that the total effect of being highly leveraged, small, and small and young is negative and significant.

Table 9: Deleveraging during the Great Recession

	(1)	(2)	(3)	(4)	(5)	(6)
$SMALL_i \times POST_t$	0.000637		0.00524			
	(0.00474)		(0.0048)			
$HL_i \times POST_t$		–0.177	–0.0949	–0.0948	–0.162	–0.0914
		(0.00753)	(0.0201)	(0.0202)	(0.0129)	(0.0138)
$HL_i \times SMALL_i \times POST_t$			–0.0828			
			(0.0216)			
$SYOUNG_i \times POST_t$				0.00894	0.00314	0.0066
				(0.00503)	(0.00274)	(0.00508)
$SOLD_i \times POST_t$				0.00406	–0.00187	0.00161
				(0.00485)	(0.00229)	(0.00492)
$HL_i \times SYOUNG_i \times POST_t$				–0.113	–0.0458	–0.0423
				(0.027)	(0.0224)	(0.0169)
$HL_i \times SOLD_i \times POST_t$				–0.0665	0.0013	–0.00725
				(0.0212)	(0.0145)	(0.0143)
$COLLAT_i \times POST_t$	0.0266	0.0203	0.0203	0.0206	0.0207	0.00997
	(0.00421)	(0.0042)	(0.0042)	(0.00425)	(0.00432)	(0.00422)
$PROFIT_i \times POST_t$	0.00869	0.00117	0.00113	–0.0000171	–0.0000024	0.00113
	(0.00332)	(0.00307)	(0.00307)	(0.00302)	(0.00302)	(0.00308)
$RG_i \times POST_t$	0.00217	0.00315	0.00317	0.00254	0.00254	0.00189
	(0.00272)	(0.00251)	(0.00251)	(0.00253)	(0.00253)	(0.00253)
leverage thresh.	33%	33%	33%	33%	33%	15%
emp thresh.	500	500	500	500	100	500
age thresh.	10	10	10	10	10	10
observations	270000	270000	270000	270000	270000	270000
firm count	72000	72000	72000	72000	72000	72000
r-squared	0.5674	0.5826	0.5826	0.5829	0.5828	0.5817
F-test (high lev.)			0	0	0	0
F-test (small)			0.0002	0.0001	0.1728	0.1438
F-test (small-young)				0.0001	0.0528	0.0277
F-test (small-old)				0.0027	0.9683	0.6806

Notes: We consider a pooled sample privately-held and publicly-traded LOCUS firms between 2005 and 2012. The dependent variable is short-term leverage. All regressors are defined at the firm level by their value in the first year we observe the firm in LOCUS. The regressors of interest are: small firm indicator (or broken into small-young and small-old) interacted with a post indicator (= 1 in 2009-2012), high leverage indicator interacted with the post dummy, and the triple interaction. We also control for collateral, profitability, and the DHS revenue growth rate, all defined in the same way as the indicators and interacted with the post dummy. All regressions include firm, 4-digit×year, and county×year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample. Standard errors are clustered at the firm level.

3.3 Deleveraging Firms and Employment Growth

To better understand the extent to which firm deleveraging affects real outcomes, we directly evaluate the relationship between leverage and firm employment growth during the financial crisis. Motivated by the evidence that firm leverage, in conjunction with firm life-cycle characteristics, is informative about post-shock deleveraging, we consider the following specification that parallels Equation (7), but uses log employment as the dependent variable:

$$\begin{aligned}\log(EMP_{it}) =& \alpha_i + (\omega_s \times \lambda_t) + (\phi_c \times \lambda_t) + \beta_1(SMALL_i \times POST_t) + \\ & \beta_2(HL_i \times POST_t) + \beta_3(HL_i \times SMALL_i \times POST_t) + \\ & \mathbf{\Gamma}'(Z_i \times POST_t) + \epsilon_{it}\end{aligned} \tag{8}$$

where the right hand side variables are specified exactly as in Equations (6) and (7).

The results in Table 10 reveal that deleveraging does not translate into lower employment growth for the average firm. Recall that in Table 9, we document that all highly leveraged firms deleverage after the credit shock, though highly leveraged small firms (and especially highly leveraged small-young firms) deleverage much more. In column (2) of Table 10 we find that highly leveraged firms grow 5% lower during the crisis and column (3) reveals that this effect is entirely driven by highly leveraged small firms, which grow 11% less. Digging further into the results, we find in column (4) that highly leveraged small-young firms experience 21% lower employment growth.

Taken together, the results in Tables 9 and 10 provide two key insights. First, highly leveraged firms become constrained when aggregate credit conditions tighten if they are small, or small and young. Second, employment growth among these firms becomes significantly lower. One explanation is that the shock tightens these firms' borrowing constraints, and since they cannot borrow more to smooth out the shock, they experience lower employment growth and at the same time deleverage by reducing debt.

Table 10: Employment Growth during the Great Recession

	(1)	(2)	(3)	(4)	(5)	(6)
$SMALL_i \times POST_t$	0.0636		0.0700			
	(0.0244)		(0.0253)			
$HL_i \times POST_t$		–0.0483	0.069	0.0701	–0.00153	0.0433
		(0.0183)	(0.0675)	(0.0696)	(0.0322)	(0.0454)
$HL_i \times SMALL_i \times POST_t$			–0.119			
			(0.0697)			
$SYOUNG_i \times POST_t$				0.164	0.185	0.166
				(0.0274)	(0.015)	(0.0287)
$SOLD_i \times POST_t$				0.0329	0.0533	0.0324
				(0.0254)	(0.0109)	(0.0266)
$HL_i \times SYOUNG_i \times POST_t$				–0.230	–0.154	–0.135
				(0.0822)	(0.0562)	(0.0538)
$HL_i \times SOLD_i \times POST_t$				–0.0729	–0.00392	–0.0368
				(0.0709)	(0.035)	(0.0464)
$COLLAT_i \times POST_t$	–0.0155	–0.0166	–0.0171	–0.0237	–0.0321	–0.0256
	(0.0188)	(0.0188)	(0.0188)	(0.0186)	(0.0189)	(0.0187)
$PROFIT_i \times POST_t$	0.0479	0.0460	0.0458	0.0341	0.0333	0.0362
	(0.0155)	(0.0154)	(0.0154)	(0.0153)	(0.0154)	(0.0154)
$RG_i \times POST_t$	0.155	0.155	0.155	0.126	0.127	0.126
	(0.0146)	(0.0146)	(0.0146)	(0.0147)	(0.0147)	(0.0147)
leverage thresh.	33%	33%	33%	33%	33%	15%
emp thresh.	500	500	500	500	100	500
age thresh.	10	10	10	10	10	10
observations	270000	270000	270000	270000	270000	270000
firm count	72000	72000	72000	72000	72000	72000
r-squared	0.9424	0.9424	0.9424	0.9428	0.9428	0.9428
F-test (high lev.)			0.0072	0.0052	0.0061	0.0194
F-test (small)			0.466	0.4489	0.3021	0.7493
F-test (small-young)				0.4033	0.5684	0.5115
F-test (small-old)				0.5541	0.1458	0.9135

Notes: We consider a pooled sample privately-held and publicly-traded LOCUS firms between 2005 and 2012. The dependent variable is log firm employment. All regressors are defined at the firm level by their value in the first year we observe the firm in LOCUS. The regressors of interest are: small firm indicator (or broken into small-young and small-old) interacted with a post indicator (= 1 in 2009-2012), high leverage indicator interacted with the post dummy, and the triple interaction. We also control for collateral, profitability, and the DHS revenue growth rate, all defined in the same way as the indicators and interacted with the post dummy. All regressions include firm, 4-digit×year, and county×year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample. Standard errors are clustered at the firm level.

3.4 An Assessment of Aggregate Effects

To obtain an estimate of the aggregate effect of deleveraging on firm growth when aggregate credit conditions tighten, we combine publicly available data from the U.S. Census Bureau's Business Dynamic Statistics (BDS) with our estimation results. We note that our regressions are estimated using a sample of firms that existed in 2008 and continue to exist during at least a portion of the 2008-2010 period. Consequently, the estimates we provide in this section are likely lower bounds for the aggregate effects because we do not take into account the contribution of changes in employment from entry and exit, if the shock lowers entry and induces more exit.

We begin by using the BDS to obtain three pieces of information:

1. Total U.S. firm employment in 2008 in firms that *continue* into 2009 or 2010 (TE_0).

2. The share of U.S. firm employment in small *continuing* firms during the pre-crisis period, which is measured as the average share of employment in *continuing* firms with less than 500 employees between 2005 and 2008 ($Ssmall_0$).

3. Excess job loss during the 2008-2010 period. To calculate this figure, we calculate the average 3-year change in employment in the pre-period for continuing firms (e.g., the average of the change in employment of *continuing* firms between 2003-2005, 2004-2006, 2005-2007, and 2006-2008) (ΔTE_{pre}), and the 3-year change in employment in the first part of the post-period (2008-2010), again for *continuing* firms ($\Delta TE+_{post}$). We refer to the difference as the excess job loss ($EJL_{GR} = \Delta TE +_{post} - \Delta TE_{pre}$).

We then use our LOCUS estimation sample to obtain two pieces of information:

1. The weighted employment share of highly leveraged firms among all firms, using the first observed employment of each firm in our sample in the pre-period ($Semp_{HL}$).

2. The weighted employment share of highly leveraged small firms among all firms, using the first observed employment of each firm in our sample in the pre-period ($Semp_{HLsmall}$).

We then combine the BDS and LOCUS data with the coefficients on $HL \times POST$ and $HL \times SMALL \times POST$ (from Table 10) to document the fraction of aggregate excess job loss accounted for by highly leveraged and highly leveraged small firms. Specifically, we calculate, respectively:

$$EJL_{HL} = \frac{TE_0 \times Semp_{HL} \times \hat{\beta}_{HL \times POST}}{EJL_{GR}} \tag{9}$$

$$EJL_{HLsmall} = \frac{TE_0 \times Ssmall_0 \times Semp_{HLsmall} \times \hat{\beta}_{HL \times SMALL \times POST}}{EJL_{GR}} \tag{10}$$

Using Equation (9) we estimate that although highly leveraged firms in our sample account for 5% of total employment, they only account for 3% of excess job loss during the Great Recession. While this estimate suggest that the deleveraging channel may account for a disproportionately small share of excess job loss, this number ignores that our estimates in Table 10 highlight that the job loss of highly leveraged firms were concentrated among *small* firms.

Using Equation (10) we estimate that although highly leveraged small firms in our sample account for only 3% of total employment, they account for 5% of excess job loss. This estimate highlights the importance of the heterogeneity in responsiveness of highly leveraged firms to tightening credit conditions.

Thus far, we have estimated only the aggregate effect of the deleveraging of highly leveraged firms on excess job loss during the Great Recession. However, even though small firms account for 50% of employment, they actually accounted for a higher share (55%) of excess job loss in the post financial crisis period. Among these especially affected firms, highly leveraged small firms account for 6% of employment, but 10% of excess job loss among small firms.[25]

Among small firms, the job loss was disproportionately concentrated among small-young firms. The small-young firms accounted for 38% of pre-crisis small firm employment, but 42% of small firm job loss during the financial crisis. Among the small-young firms, 7% of employment is accounted for by those that are highly leveraged, yet they account for 18% of small-young firm job loss during the crisis.[26]

Ultimately, our assessment of the aggregate effects highlights the importance of properly accounting for heterogeneous effects. Highly leveraged small firms, and especially highly leveraged small-young firms, account for a disproportionate share of excess job loss following the Great Recession. It is important to emphasize that our calculations are

[25] The 10% is calculated using a modified version of Equation (10), where the aggregate excess job loss during the Great Recession in the denominator is replaced with the small firm excess job loss.

[26] 18% is based on a modified version of Equation (10): $EJL_{HLsmall} = \frac{TE_0 \times Ssmall_0 \times Semp_{HLsmall-young} \times \hat{\beta}_{HL \times SYOUNGH \times POST}}{EJL_{small-young,GR}}$.

lower bound because general equilibrium effects that are most likely to work via entry and exit are not accounted for—if the shock adversely affects entry and induces more exit.

4 Conclusion

Privately-held firms play a key role in the U.S. economy, accounting for 75% of aggregate employment and 54% of aggregate gross output on average over the past two decades. Small-young firms, which account for 20% of U.S. employment and are primarily privately owned, are particularly important for business dynamism and job creation. An extensive literature in macroeconomics argues that small firms' deteriorating financial conditions can have a significant adverse impact on the overall economy. An equally extensive finance literature shows small firms are financially constrained. However systematic evidence linking these two strands of literature has been lacking.

We create a novel dataset by merging the Census Bureau's LBD with firm-level financial data from Moody's Orbis. Using this dataset and employing weights aimed at representing the U.S. firm population, we show that financial frictions vary over a firm's life-cycle, and the impact of a credit shock on aggregate employment critically depends on firm-level heterogeneity in financial frictions. Specifically, where the firm is in its life-cycle at the onset of the shock tells us a) whether that firm's growth will be impacted by the shock, and b) how much of the effects on aggregate employment will come from the impacted financially-constrained firms.

Our findings also have implications on declining business dynamism and policies that try to revive aggregate growth. The findings suggest that highly-leveraged, small and young firms are especially susceptible to changes in aggregate financial conditions. Because entry generally relies on debt-financed startup funding, our results suggest that following a financial crisis, it may take some time for the number of small-young firms in the economy to rebound, an effect that may show up as reduced business dynamism and lower aggregate growth.

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Appendix — For Online Publication

A Calculating Contribution of Publicly-Traded Firms

We evaluate the contribution of publicly-traded firms to the aggregate (i) firm count, (ii) employment, and (iii) revenue. Because our analysis focuses on the private, non-financial firms, when calculating aggregate variables, we also restrict ourselves to the private, non-financial sector (e.g., we exclude NAICS codes 52 and 92 from our analysis).

The aggregate number of firms and total employment are both obtained from the U.S. Census Bureau's Business Dynamic Statistics (BDS). Specifically, we use the "sector" one-way dataset that allows us to drop the financial sector (NAICS code 52).[27] Total gross output is obtained from the BEA's Industry Economic Accounts. The current vintage of these industry accounts is only available for 2017–2022, we therefore use the 2017 vintage that covers the period 2005–2012. For each year, we measure total private, non-financial (i.e., exclude NAICS codes 52 and 92) gross output in the fourth quarter. Gross output measure revenue, including both final users and other industries.

As discussed in the main text, calculating the contribution of publicly-traded firms to the U.S. economy is challenging in part because Compustat does not identify which firms operate establishments located within the United States. Here, we report the contribution of publicly-traded firms using four different approaches to identifying firms that likely operate in the U.S.:

- **Preferred Measure**: firms must satisfy at least one of the following criteria
  - Headquartered in the United States (i.e., reports a U.S. address).
  - Reports an Employer Identification Number (EIN), which is required for payroll and sales taxes.
  - Lists the United States as one of its markets. We determine this based on whether one of two criteria are met: (i) the Compustat Segements data lists

[27] The BDS data does not include activity from NAICS code 92.

"USA" as a market; (ii) the business description variable in Compustat includes the work "United States," "USA," or "US."

- **Alternative 1**: firms that are incorporated in the United States (i.e., the variable *fic* takes the value "USA").
- **Alternative 2**: firms that are headquartered in the United States (i.e., the variable *loc* takes the value "USA").
- **Alternative 3**: firms that are *either* incorporated or headquartered in the United States (i.e., either *fic* or *loc* take the value "USA").

In Table A.1, we report the average (2005-2012) contribution of publicly-traded firms to the aggregate (i) number of firms, (ii) employment, and (iii) revenue separately for each "raw" measure discussed above. We also report the contribution of the "active" subset of these firms, where a firm is determined to be actively traded as long as it has a positive security price in a particular year or in the years that bracket that year (following Davis et al. (2006)). Finally, we report the "adjusted" contribution of the "active" subset of firms (i.e., "active & adjusted"). This last measure accounts for the fact that Compustat reports total number of employees and revenue of both domestic and foreign subsidiaries. We approximate domestic employment and revenue by adjusting the Compustat totals by a factor of 0.7109 for employment and 0.8070 for revenue. These adjustment factors represent the 2005 to 2012 average fraction of LBD-to-Compustat employment and revenue calculated using LOCUS, respectively.

The results in Table A.1 show that publicly-traded firms that operate in the U.S. and are actively traded contribute between 0.09 to 0.1% of firms (column 2), between 22 to 25% of domestic employment (column 5), and between 40 and 46% of gross output (column 8). It is worth noting that our preferred measure represents the loosest criteria, and results in the highest (across the four measures) contribution of publicly-traded firms to the U.S. economy.

Table A.1: Contribution of publicly-traded Firms to Aggregate Economic Activity (%)

	Firms		Employment			Gross Output		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	raw	active	raw	active	active & adjusted	raw	active	active & adjusted
preferred	0.118	0.102	38.3	35.4	25.2	63.5	57.5	46.4
incorporated	0.109	0.093	33.2	30.6	21.7	54.8	49.4	39.8
located	0.108	0.092	33.4	30.8	21.9	55.5	50.0	40.3
incorp or loc	0.112	0.096	33.7	31.1	22.1	55.8	50.2	40.5

Notes: The table reports the percentage contribution of publicly-traded firms to total firms (cols. 1 and 2), total employment (cols. 3 to 5), and total gross output (cols. 6 to 8). Cols. 1, 3, and 6 consider publicly-traded firms that (likely) operate domestically, based on either our preferred criteria (row 1), being incorporated in the US (row 2), being headquartered in the US (row 3), and being located or headquartered in the US (row 4). Cols 2, 4, and 7 restrict only to actively publicly-traded firms. Cols. 5 and 8 additionally approximate the domestic (US) portion of Compustat employment (adjustment factor = 0.7109) and revenue (adjustment factor = 0.8070), using adjustment factors calculated using LOCUS.

B Constructing the LOCUS Dataset

B.1 Matching Procedure

The LBD-BR is linked to Orbis and Compustat separately using a multi-step procedure.

Step 1. Preparing Data for Matching: We separately prepare the LBD-BR, Orbis and Compustat for matching. For each of the datasets, we keep the "target" set of observations (entity-years) and variables used in the matching procedure. We then standardize and create matchcodes for string variables.

In LBD-BR, our target set of establishment-year observations consists of those with valid establishment and firm identifiers, non-missing employment, and positive payroll. The LBD-BR contains time-varying information on EIN, entity name, street address, city, state, and zip code. We run firm name, street address, and city variables through a common string standardization procedure. Using SAS's DQMATCH, we create matchcodes for firm name, street address, and city using a sensitivity of 80.

In Compustat, we end up with a target set of about X0 firms and Y0 observations. Starting with the raw data, we obtain our target set as follows. We focus on industrial financial statements and deduplicate the data to end up with one observation per EIN-year, which also yields one observation per GVKEY-year. We drop firms that are not actively traded, and firms that do not have an EIN *and* do not list a US address. We also drop firms with NAICS codes equal to 11 (Agriculture), 52 (Finance and Insurance), 813 (Religious, Grantmaking, Civic and Professional Organizations), 92 (Public Administration), and 99 (Nonclassifiable Establishments). Compustat contains time-invariant (latest available) information on EIN, firm name, street address, city, state and zip code. We run firm name, street address, and city information through a common string standardization procedure. Using SAS's DQMATCH, we create matchcodes for firm name, street address, and city using a sensitivity of 80.

In Orbis, we end up with a target set of around A0 firms and B0 observations. Starting with the raw data, we obtain our target set as follows. We first deduplicate by keeping only one type of account (consolidated or unconsolidated) for each BVDD over time, with a preference given to unconsolidated accounts. We drop firms in NAICS codes 11, 52, 813, 92, and 99. Orbis contains time-invariant (latest available) information on EIN, firm name, city, state, and zip code. We run firm name and city through a common string standardization procedure. Using SAS's DQMATCH, we create matchcodes from firm name and city using a sensitivity of 80. It is worth noting that because Orbis includes both publicly-traded and privately-held firms, there is some overlap in firms (and observations) between the Orbis and Compustat data. This overlap is addressed below in section B.3.

Step 2. Iterative Matching: We separately performing matching with replacement between (i) LBD-BR and Compustat and (ii) LBD-BR and Orbis.

The LBD-BR and Compustat match consists of 62 matching passes based on increasingly less stringent criteria. The most stringent match pass is *enacsz5*, which is based on EIN (*e*), firm name matchcode (*n*), street address matchcode (*a*), city matchcode (*c*), state (*s*), and 5-digit zip code (*z5*). The least stringent match passes are based on street address matchcode only (pass 61) and firm name matchcode only (pass 62). The match pass is kept track of in a separate variable.

The LBD-BR and Orbis match only contains 27 match passes because Orbis does not contain street address information. The most stringent match pass is *encsz5*, which is based on EIN (*e*), firm name matchcode (*n*), city matchcode (*c*), state (*s*), and 5-digit zip code (*z5*). The least stringent match pass is based only on the firm matchcode (pass 27).

Step 3. Finalizing Matched Data: We separately finalize (i) LBD-BR and Compustat and (ii) LBD-BR and Orbis matches in three steps.

Step 3a. Deduplicating by ID-year: We deduplicate matches separately for each year an entity is observed in the financial (Compustat/Orbis) data. For each year, we first keep only matches made to LBD-BR records that are active in that year.

Next, we create an adjusted match pass, and keep adjusted matches made on (at minimum) (i) EIN or (ii) name and at least one address variable. To do so, we first create Jaro-Winkler scores that compare Compustat/Orbis and LBD-BR firm name, street address (Compustat only), and city. For each, we replace the Jaro-Winkler score as missing (i.e., not matched on) if that score is below a threshold value that is chosen based on clerical review. We then use the updated information to create an adjusted match pass. At this point, we exclude matches based only on address (Compustat) or only on firm name.[28]

We then keep only the highest quality LBD-BR match(es) for each Compustat/Orbis entity in each year. Specifically, we keep matches based on the lowest (most stringent) adjusted match pass. If needed, we further deduplicate by choosing matches based on NAICS code, employment and/or revenue similarity (Compustat/Orbis vs. LBD-BR).

Step 3b. Cleaning Longitudinal Links: We stack the annually deduplicated matched data and evaluate its longitudinal consistency. We end up with a panel that assigns a unique LBD-BR firm identifier for each Compustat/Orbis firm by year observation.

Starting with the pre-match Compustat/Orbis panel, we merge in the deduplicated stacked matched data, and categorize Compustat/Orbis firms into four groups: (1) matched to the same LBD-BR firm identifier consistently over time; (2) matched to only one LBD-BR firm identifier, with gaps (i.e., match in some years but not others); (3) matched to more than one LBD-BR firm identifier, with no gaps; and (4) matched to more than one LBD-BR firm identifier, with gaps.

[28]Suppose that a Compustat record matched to the LBD-BR in match pass 1 during iterative matching (*enacsz5*). However, using Jaro-Winkler, we find that the score for the street address falls below the defined threshold. We no longer consider the record to be matched on street address, which means that the adjusted match pass will now be match pass 10 (*encsz5*).

We perform imputation for firms in groups 2 through 4. For firms in group 2, we simply impute the LBD-BR firm identifier in the missing years because Compustat/Orbis firms in this group only match to a single LBD-BR firm, but with gaps. For firms in groups 3 and 4, the imputation procedure is slightly more complicated. For each year of the Compustat/Orbis data, we choose a (sometimes) new LBD-BR matching firm based on whether that matching firm is active in that year and has the highest overall match quality. Here, we measure quality by (i) the lowest (most stringent) adjusted match pass, (ii) NAICS code similarity, (iii) average employment similarity, (iv) average revenue similarity, and (v) number of matching years. This procedure reduces, but does not necessarily eliminate, the number of LBD-BR firms that a Compustat/Orbis firm matches to over time. We drop Compustat/Orbis firms if they match to more than four LBD-BR firms over the period 2005 through 2012.

Step 3c. Deduplicating by LBD identifier-year: As a final step, we make necessary adjustments to ensure that the panel data is also unique in LBD-BR firm by year.

In the rare case where a LBD-BR firm matches to multiple Compustat/Orbis firms in a year, we keep only the highest quality match. The quality of the match is (again) measured by (i) the lowest (most stringent) adjusted match pass, (ii) NAICS code similarity, (iii) average employment similarity, (iv) average revenue similarity, and (v) number of matching years.

B.2 Matching Assessment

After implementing the steps described above, we end up matching 81% of observations and firms in Compustat, and 69% of firms and 77% of observations in Orbis. The vast majority of matches were made in part based on EIN: 75% for Compustat and 78% for Orbis. Matches made based on the combination of firm name and address information represent 21% of matches for both Compustat and Orbis. The small remainder, 4% for Compustat and 1% for Orbis, are based on the imputation steps described above.

B.3 Combining the Matched Data

In order to finalize LOCUS, we need to combine the separate, cleaned matches for (i) Compustat and LBD-BR and (ii) Orbis and LBD-BR, and bring in the financial statement variables.

Because financial data comes from either Compustat or Orbis, we first ensure that the data are reported consistently across the two sources. Specifically, we (i) redefine a few variables in Compustat to make them consistent with the way the corresponding variables are defined in Orbis (ex: current loans is debt due in one year); (ii) transform Orbis variables into USD millions; and (iii) deflate Compustat and Orbis financial variables.

Next, we combine the cleaned Compustat and Orbis matches. From LBD we retain information on number of employees, payroll, industry (modal), location (county with the highest employment), and revenue (available only at the firm level). For each mached LBD-BR firm-year observation, we bring in financial statement variables from either Compustat or Orbis, depending on the source of the match. Because Orbis contains both publicly-traded and privately-held firms, if a LBD-BR firm matches to both a Compustat and Orbis firm, we give preference to Compustat as the source of financial data. Note also that we ensure the source of financial data for each matched LBD-BR firm is consistent (either Compustat or Orbis) over time.

B.4 Cleaning the LOCUS Data

In preparing the LOCUS data for analysis, We closely follow the data cleaning procedure described in the online appendix of Gopinath et al. (2017). We clean the data in three steps: we (i) clean basic reporting mistakes, (ii) verify the internal consistency of key balance sheet variables, and (iii) construct variables of interest and winsorize the data.

Cleaning Basic Reporting Mistakes:

The first step of data cleaning is applied to both Compustat and Orbis financial data. Specifically:

1. Drop firm-year observations if total assets, revenue, and employment (from LBD) are missing.

2. Drop firm-year observations if revenue or total assets is negative, zero, or missing.

3. Drop firms if total assets, revenue, tangible fixed assets, or employment (LBD) are negative in any year. Also drop firms if employment (LBD) is greater than 2 million in any year.

Verifying Internal Consistency of Balance Sheet Data:

The second step of data cleaning is only applied to Orbis financial data. The reason being that publicly-traded firms in Compustat are subject to strict regulatory financial reporting requirements, unlike the privately-held firms in Orbis.

To verify internal consistency of balance sheets, we construct ratios where the numerator is the sum of variables that belong to an aggregate and the denominator is the respective aggregate variable.

1. The sum of tangible fixed assets, intangible fixed assets, and other fixed assets divided by total fixed assets. We drop firm-year observations where the ratio is smaller than 0.875 or higher than 1.125.

2. The sum of stocks, debtors, and other current assets divided by total current assets. We drop firm-year observations where the ratio is smaller than 0.875 or higher than 1.125.

3. The sum of fixed assets and current assets divided by total assets. We drop firm-year observations where the ratio is smaller than 0.9 or higher than 1.1.

4. The sum of capital and other shareholder funds divided by total shareholder funds. We drop firm-year observations where the ratio is smaller than 0.875 or higher than 1.125.

5. The sum of long term debt and other non-current liabilities divided by total non-current liabilities. We drop firm-year observations where the ratio is smaller than 0.875 or higher than 1.125.

6. The sum of current loans, current creditors, and other current liabilities divided by total current liabilities. We drop firm-year observations where the ratio is smaller than 0.875 or higher than 1.125.

7. The sum of non-current liabilities, current liabilities, and shareholder funds divided by the variable that reports the sum of shareholder funds and total liabilities. We drop firm-year observations where the ratio is smaller than 0.9 or higher than 1.1.

Because privately-held firms do not report a separate "liabilities" variable, we create two versions of the variable. The first is measured as the variable that reports the sum of shareholder funds and total liabilities minus shareholder funds. The second is measured as the sum of non-current liabilities and current liabilities. We take the ratio of the two variables and drop firm-year observations where the ratio is smaller than 0.9 or higher than 1.1.

Following the approach of Diez, Fan and Villegas-Sanchez (2021), we drop firms that in any year have above the 99.9th percentile in one-year revenue (Orbis) growth. This step is meant to clean large "jumps" in the data that are likely caused by reporting errors.

Creating Analysis Data:

Our cleaned LOCUS data contains 166,400 unique firms, 96% of which are privately-held. To create our analysis data, we define the following variables using data from financial statements:

- Short-term leverage is defined as current loans divided by total assets.
- Long-term leverage is defined as long-term debt divided by total assets.
- Financial leverage is defined as current loans plus long-term debt divided by total assets.
- Collateral is defined as tangible fixed assets over total assets.
- Liquidity is defined as cash over total assets.
- Profitability is defined as net income over total assets.

- Size is measured as log of total assets. Note that this measure of size is only used for robustness.

Note that all financial variables that are defined as ratios are winsorized at the 1st and 99th percentiles.

We also define the following variables using data from LBD:

- Size is defined as log of firm employment. Note that this is our preferred measure of size.
- Firm age is defined based on the first operating year of the oldest establishment owned by the firm.
- Revenue growth is defined as the DHS growth rate of firm revenue.
- Firm industry is defined based on the modal industry and is defined to be time invariant.
- Firm county is defined based on the county with the largest employment, and is also defined to be time invariant.

C Accounting for Selection (Additional Output)

The figure and tables below demonstrate how applying propensity weights reduces the observable differences between reporting and non-reporting privately-held firms in terms of employment growth, multi-unit status and legal form.

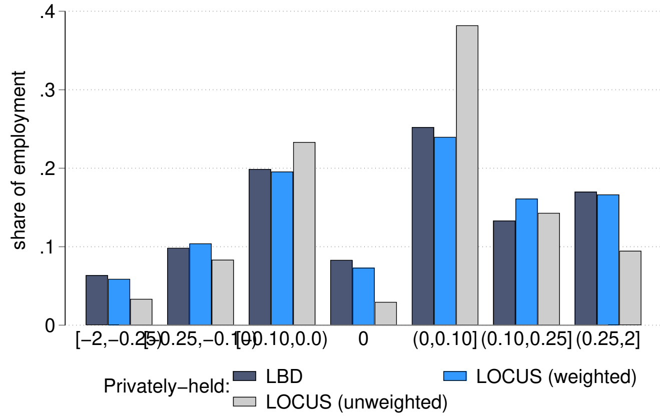

Figure C.1: Firm Employment Growth Distributions (% of emp)

Notes: This figure compares the fraction of sample firm-level employment accounted for by each employment growth group. Each bar represents a different sample. The first bar represents all private, non-financial employer businesses in the LBD. The second bar represents the weighted LOCUS sample of privately-held firms, where the weights are derived from estimating equations (3) through (5). The third bar represents the unweighted LOCUS sample of privately-held firms, where each firm gets equal weight.

Table C.1: Multi-unit Status Distributions (% of emp)

	(1)	(2)	(3)
Privately-held:	LBD	LOCUS (weighted)	LOCUS (unweighted)
Single-unit	0.59	0.53	0.27
Multi-unit 0.41	0.47	0.73	

Notes: This table compares the fraction of sample firm-level employment accounted for by single- and multi-unit firms. Each column represents a different sample. The first column represents all private, non-financial employer businesses in the LBD. The second column represents the weighted LOCUS sample of privately-held firms, where the weights are derived from estimating equations (3) through (5). The third column represents the unweighted LOCUS sample of privately-held firms, where each firm gets equal weight.

Table C.2: Legal Form Distributions (% of emp)

Privately-held:	(1) LBD	(2) LOCUS (weighted)	(3) LOCUS (unweighted)
Corporation	0.39	0.40	0.32
S-corp, sole-prop & partner.	0.35	0.44	0.15
Other	0.26	0.16	0.52

Notes: This table compares the fraction of sample firm-level employment accounted for by each legal form group. Each column represents a different sample. The first column represents all private, non-financial employer businesses in the LBD. The second column represents the weighted LOCUS sample of privately-held firms, where the weights are derived from estimating equations (3) through (5). The third column represents the unweighted LOCUS sample of privately-held firms, where each firm gets equal weight.

D Robustness

Table D.1: Financial Leverage: Alternative Fixed Effects

	Year FE			Industry x Year FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	private	public	all	private	public
log(EMP_{it})	0.0256	0.0259	0.0178	0.0214	0.0217	0.0168
	(0.00232)	(0.00236)	(0.00165)	(0.00279)	(0.00285)	(0.0029)
AGE_{it}	–0.00239	–0.00240	0.000116	–0.00273	–0.00274	0.00057
	(0.000296)	(0.000297)	(0.000207)	(0.00032)	(0.000321)	(0.00053)
$COLLAT_{it}$	0.236	0.236	0.279	0.225	0.225	0.220
	(0.0207)	(0.0208)	(0.0102)	(0.0176)	(0.0177)	(0.0368)
$PROFIT_{it}$	–0.0693	–0.0694	–0.187	–0.0685	–0.0685	–0.194
	(0.0057)	(0.0057)	(0.0112)	(0.0069)	(0.0069)	(0.0156)
RG_{it}	0.0048	0.00485	–0.0160	0.00464	0.00466	–0.0107
	(0.00386)	(0.00386)	(0.00327)	(0.00301)	(0.00301)	(0.00454)
yr FE	Y	Y	Y	N	N	N
county x yr FE	N	N	N	N	N	N
4-digit x yr FE	N	N	N	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA
observations	357500	338000	19500	357500	338000	19500
firm count	142300	138000	4300	142300	138000	4300
r-squared	0.0916	0.0918	0.1255	0.1684	0.1685	0.2047
ME log(size)	0.1986	0.1994	0.1993	0.1661	0.1671	0.1886
ME firm age	–0.153	–0.1533	0.0055	–0.1748	–0.1751	0.0271

Notes: The dependent variable is financial debt/total assets. The main regressors are log(EMP_{it}) (firm size); AGE_{it} (firm age); $COLLAT_{it}$ (tangible fixed assets over total assets); $PROFIT_{it}$ (net income over total assets); and RG_{it} (DHS revenue growth). Columns (1)-(3) include year fixed effects and columns (4)-(6) include industry×year fixed effects. The years are 2005–2012. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the industry and year level.

Table D.2: Financial Leverage: Alternative Controls

	Total Assets			Cash/Total Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	private	public	all	private	public
log(EMP_{it})				0.0124	0.0126	0.0129
				(0.00219)	(0.00225)	(0.0028)
log(TA_{it})	0.0127	0.0128	0.0184			
	(0.00183)	(0.00187)	(0.00277)			
AGE_{it}	–0.00224	–0.00224	0.000443	–0.00250	–0.00251	–0.000304
	(0.000237)	(0.000237)	(0.000461)	(0.000256)	(0.000257)	(0.00049)
$COLLAT_{it}$	0.212	0.212	0.210	0.159	0.160	0.158
	(0.0199)	(0.02)	(0.0355)	(0.0235)	(0.0236)	(0.0361)
$PROFIT_{it}$	–0.0611	–0.0610	–0.219	–0.0530	–0.0530	–0.205
	(0.00584)	(0.00583)	(0.0165)	(0.006)	(0.00599)	(0.0144)
RG_{it}	0.00219	0.00217	–0.0129	0.00244	0.00245	–0.0101
	(0.00353)	(0.00353)	(0.00518)	(0.00322)	(0.00322)	(0.00507)
CTA_{it}				–0.186	–0.186	–0.279
				(0.0132)	(0.0132)	(0.032)
county x yr FE	Y	Y	Y	Y	Y	Y
4-digit x yr FE	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA
observations	357500	338000	19500	357500	338000	19500
firm count	142300	138000	4300	142300	138000	4300
r-squared	0.2641	0.2624	0.2052	0.2916	0.29	0.2298
ME log(size)	0.0985	0.0989	0.2068	0.0962	0.0968	0.145
ME firm age	–0.1436	–0.1436	0.0211	–0.1603	–0.1605	–0.0144

Notes: The dependent variable is financial debt/total assets. The regressors are firm size, measured as log(TA_{it}) in columns (1)-(3) and log(EMP_{it}) in columns (4)-(6); AGE_{it} (firm age); $COLLAT_{it}$ (tangible fixed assets over total assets); $PROFIT_{it}$ (net income over total assets); RG_{it} (DHS revenue growth); and additionally CTA_{it} (cash over total assets) in columns (4)-(6). All regressions include both industry×year and county×year fixed effects. The years are 2005–2012. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the ind. and year level.

Table D.3: Short-term & Long-term Leverage: Alternative Fixed Effects

	Year FE						Industry x Year FE					
	Short-term Leverage			Long-term Leverage			Short-term Leverage			Long-term Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	all	private	public	all	private	public	all	private	public	all	private	public
$\log(\text{EMP}_{it})$	0.00958	0.00983	–0.00137	0.0185	0.0186	0.0193	0.00990	0.0102	–0.00224	0.0140	0.0140	0.0194
	(0.000987)	(0.00101)	(0.000278)	(0.0017)	(0.00173)	(0.0016)	(0.00118)	(0.00121)	(0.000605)	(0.00222)	(0.00227)	(0.00272)
AGE_{it}	–0.000281	–0.000284	0.00000111	–0.00220	–0.00220	0.000127	–0.000425	–0.000428	0.0000389	–0.00242	–0.00242	0.000519
	(0.0000583)	(0.0000584)	(0.0000491)	(0.000278)	(0.000279)	(0.000187)	(0.0000698)	(0.0000698)	(0.000101)	(0.000301)	(0.000302)	(0.00046)
COLLAT_{it}	–0.0475	–0.0474	0.0248	0.260	0.261	0.250	–0.0406	–0.0403	0.0344	0.243	0.243	0.179
	(0.00485)	(0.00485)	(0.0023)	(0.0209)	(0.0209)	(0.00889)	(0.0071)	(0.00707)	(0.00796)	(0.0195)	(0.0195)	(0.0337)
PROFIT_{it}	–0.0262	–0.0262	–0.0681	–0.0421	–0.0421	–0.115	–0.0249	–0.0250	–0.0697	–0.0426	–0.0426	–0.121
	(0.00255)	(0.00256)	(0.00499)	(0.00504)	(0.00504)	(0.00575)	(0.00323)	(0.00323)	(0.00647)	(0.00567)	(0.00567)	(0.00944)
RG_{it}	0.0015	0.00153	–0.00540	0.00487	0.00489	–0.00910	0.000694	0.00072	–0.00486	0.00523	0.00522	–0.00434
	(0.00208)	(0.00208)	(0.00156)	(0.0024)	(0.0024)	(0.00376)	(0.00175)	(0.00175)	(0.00209)	(0.00206)	(0.00206)	(0.0043)
yr FE	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N
county x yr FE	N	N	N	N	N	N	N	N	N	N	N	N
4-digit x yr FE	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA	Y	Y	NA	Y	Y	NA
observations	357500	338000	19500	332500	313000	19500	357500	338000	19500	332500	313000	19500
firm count	142300	138000	4300	137300	133000	4300	142300	138000	4300	137300	133000	4300
r-squared	0.0296	0.03	0.0791	0.1161	0.1161	0.1193	0.1004	0.1008	0.0832	0.184	0.1841	0.2003
ME log(size)	0.2756	0.2804	–0.1223	0.1861	0.1857	0.2501	0.2849	0.2906	–0.1994	0.1402	0.1399	0.2514
ME firm age	–0.0665	–0.0673	0.0004	–0.1827	–0.183	0.0069	–0.1009	–0.1015	0.0147	–0.2011	–0.2014	0.0285

Notes: The dependent variables are short-term debt/total assets and long-term debt/total assets. The main regressors are $\log(\text{EMP}_{it})$ (firm size); AGE_{it} (firm age); COLLAT_{it} (tangible fixed assets over total assets); PROFIT_{it} (net income over total assets); and RG_{it} (DHS revenue growth). Columns (1)-(6) include year fixed effects and columns (7)-(12) include industry$\times$year fixed effects. The years are 2005–2012. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the industry and year level.

Table D.4: Short-term: Alternative Controls

	Short-term Leverage					
	Total Assets			Cash/Total Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	private	public	all	private	public
log(EMP_{it})				0.00693	0.00721	–0.00277
				(0.00101)	(0.00105)	(0.000667)
log(TA_{it})	0.00714	0.00735	–0.00322			
	(0.00101)	(0.00103)	(0.000656)			
AGE_{it}	–0.000315	–0.000312	0.000016	–0.000439	–0.000441	–0.000129
	(0.0000649)	(0.000065)	(0.000114)	(0.0000566)	(0.0000566)	(0.000104)
$COLLAT_{it}$	–0.0397	–0.0394	0.0389	–0.0622	–0.0618	0.0269
	(0.00579)	(0.00573)	(0.00842)	(0.00556)	(0.00553)	(0.00868)
$PROFIT_{it}$	–0.0216	–0.0216	–0.0639	–0.0190	–0.0190	–0.0699
	(0.00286)	(0.00286)	(0.00646)	(0.00276)	(0.00276)	(0.00625)
RG_{it}	–0.00132	–0.00134	–0.00422	–0.000925	–0.000903	–0.00442
	(0.002)	(0.00199)	(0.00204)	(0.00192)	(0.00192)	(0.00205)
CTA_{it}				–0.0792	–0.0790	–0.0519
				(0.0044)	(0.00438)	(0.00942)
county x yr FE	Y	Y	Y	Y	Y	Y
4-digit x yr FE	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA
observations	357500	338000	19500	357500	338000	19500
firm count	142300	138000	4300	142300	138000	4300
r-squared	0.1814	0.1797	0.0834	0.2035	0.2017	0.0891
ME log(size)	0.2054	0.2098	–0.2868	0.1993	0.2059	–0.2464
ME firm age	–0.0747	–0.074	0.006	–0.1042	–0.1046	–0.0487

Notes: The dependent variable is short-term debt/total assets. The main regressors are firm size, measured as log(TA_{it}) in columns (1)-(3) and log(EMP_{it}) in columns (4)-(6)); AGE_{it} (firm age); $COLLAT_{it}$ (tangible fixed assets over total assets); $PROFIT_{it}$ (net income over total assets); RG_{it} (DHS revenue growth); and additionally CTA_{it} (cash over total assets) in columns (4)-(6). All regressions include both industry×year and county×year fixed effects. The years are 2005–2012. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the industry and year level.

Table D.5: Pre- and Post-Great Recession: Alternative Fixed Effects

	Year FE						Industry x Year FE					
	Pre (2005-2008)			Post (2009-2012)			Pre (2005-2008)			Post (2009-2012)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	all	private	public	all	private	public	all	private	public	all	private	public
log(EMP$_{it}$)	0.0101***	0.0103***	–0.00151*	0.00878**	0.00902**	–0.00119**	0.0108***	0.0111***	–0.00244*	0.00843**	0.00868**	–0.00197**
	(0.00111)	(0.00114)	(0.000486)	(0.00209)	(0.00214)	(0.000316)	(0.0012)	(0.00123)	(0.000941)	(0.00217)	(0.00222)	(0.00055)
AGE$_{it}$	–0.000348***	–0.000352***	0.0000632	–0.000218	–0.00022	–0.0000587	–0.000472***	–0.000476***	0.0000879	–0.000384**	–0.000387**	–0.0000172
	(0.0000331)	(0.0000331)	(0.0000767)	(0.000116)	(0.000115)	(0.0000565)	(0.0000756)	(0.0000756)	(0.000126)	(0.000107)	(0.000106)	(0.000125)
COLLAT$_{it}$	–0.0528***	–0.0527***	0.0283***	–0.0385**	–0.0384***	0.0208***	–0.0485**	–0.0481**	0.0393**	–0.0268**	–0.0267**	0.0290*
	(0.006)	(0.00601)	(0.00291)	(0.00659)	(0.00654)	(0.00296)	(0.00832)	(0.00832)	(0.00941)	(0.0071)	(0.00703)	(0.00965)
PROFIT$_{it}$	–0.0278***	–0.0279***	–0.0620***	–0.0228**	–0.0229**	–0.0767***	–0.0260***	–0.0261***	–0.0628***	–0.0228*	–0.0228*	–0.0791***
	(0.0022)	(0.00219)	(0.0036)	(0.00641)	(0.00645)	(0.0103)	(0.00325)	(0.00325)	(0.00408)	(0.00719)	(0.00721)	(0.0124)
RG$_{it}$	–0.000527	–0.000481	–0.00435	0.00628	0.00628	–0.00647*	–0.000668	–0.000627	–0.00305	0.00449	0.00448	–0.007
	(0.00232)	(0.00232)	(0.00237)	(0.00406)	(0.00407)	(0.00227)	(0.00218)	(0.00218)	(0.00282)	(0.00273)	(0.00274)	(0.00305)
yr FE	Y	Y	Y	Y	Y	Y	N	N	N	N	N	N
county x yr FE	N	N	N	N	N	N	N	N	N	N	N	N
4-digit x yr FE	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA	Y	Y	NA	Y	Y	NA
observations	179500	169000	10500	177800	169000	8800	179500	169000	10500	177800	169000	8800
firm count	97800	94000	3800	98400	95500	2900	97800	94000	3800	98400	95500	2900
r-squared	0.0325	0.0329	0.0715	0.0237	0.0241	0.0897	0.093	0.0933	0.0703	0.1134	0.1139	0.0997
ME log(size)	0.268	0.2727	–0.1341	0.2799	0.2849	–0.106	0.2876	0.2933	–0.2168	0.2687	0.2742	–0.1761
ME firm age	–0.073	–0.0738	0.0226	–0.0576	–0.0582	–0.0228	–0.099	–0.0997	0.0314	–0.1016	–0.1022	–0.0067

Notes: The dependent variable is short-term debt over total assets. The main regressors are log(EMP$_{it}$) (firm size); AGE$_{it}$ (firm age); COLLAT$_{it}$ (tangible fixed assets over total assets); PROFIT$_{it}$ (net income over total assets); and RG$_{it}$ (DHS revenue growth). Columns (1)-(6) include year fixed effects and columns (7)-(12) include industry×year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. Standard errors are clustered at the industry and year level.

Table D.6: Pre- and Post-Great Recession: Alternative Controls

	Total Assets						Cash/Total Assets					
	Pre (2005-2008)			Post (2009-2012)			Pre (2005-2008)			Post (2009-2012)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	all	private	public	all	private	public	all	private	public	all	private	public
log(emp)							0.00834***	0.00866***	–0.00278*	0.00482**	0.00506**	–0.00269**
							(0.00106)	(0.0011)	(0.0011)	(0.00134)	(0.00137)	(0.000465)
firm age	–0.000300**	–0.000295**	–0.0000462	–0.000342**	–0.000340**	0.0000776	–0.000456***	–0.000458***	–0.00015	–0.000428**	–0.000430**	–0.000114
	(0.000068)	(0.0000683)	(0.000141)	(0.000104)	(0.000104)	(0.000115)	(0.0000571)	(0.0000573)	(0.000146)	(0.000102)	(0.000102)	(0.000115)
collateral	–0.0441***	–0.0436***	0.0451**	–0.0295**	–0.0293**	0.0320*	–0.0648***	–0.0644***	0.0336**	–0.0564**	–0.0562**	0.0195
	(0.00642)	(0.00637)	(0.00913)	(0.00859)	(0.00855)	(0.011)	(0.00524)	(0.00524)	(0.00935)	(0.0105)	(0.0105)	(0.0107)
profitability	–0.0217***	–0.0216***	–0.0572***	–0.0212*	–0.0211*	–0.0731***	–0.0202***	–0.0202***	–0.0623***	–0.0165*	–0.0165*	–0.0805***
	(0.00319)	(0.00319)	(0.0043)	(0.00669)	(0.00671)	(0.0122)	(0.00259)	(0.00258)	(0.00363)	(0.00656)	(0.00657)	(0.0117)
revenue growth	–0.00321	–0.00322	–0.00329	0.00386	0.00386	–0.00519	–0.00185	–0.00181	–0.00366	0.00225	0.00224	–0.00506
	(0.00252)	(0.00251)	(0.00306)	(0.00221)	(0.00221)	(0.0033)	(0.00273)	(0.00273)	(0.00305)	(0.00247)	(0.00248)	(0.0031)
log(total assets)	0.00834***	0.00858***	–0.00282*	0.00533*	0.00551*	–0.00363**						
	(0.000798)	(0.000817)	(0.00096)	(0.00174)	(0.00178)	(0.00072)						
cash/total assets							–0.0802***	–0.0800***	–0.0514**	–0.0780***	–0.0778***	–0.0523**
							(0.00512)	(0.00511)	(0.0111)	(0.00594)	(0.00589)	(0.0118)
county x yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
4-digit x yr FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
weighted	Y	Y	NA	Y	Y	NA	Y	Y	NA	Y	Y	NA
observations	179500	169000	10500	177800	169000	8800	179500	169000	10500	177800	169000	8800
firm count	97800	94000	3800	98400	95500	2900	97800	94000	3800	98400	95500	2900
r-squared	0.1672	0.165	0.0708	0.2065	0.2052	0.1001	0.1866	0.1844	0.0779	0.2326	0.2314	0.1039
ME log(size)	0.2223	0.2269	–0.2499	0.1699	0.1741	–0.324	0.2224	0.229	–0.2469	0.1537	0.1599	–0.2402
ME firm age	–0.0629	–0.0619	–0.0165	–0.0903	–0.09	0.0301	–0.0956	–0.096	–0.0536	–0.1133	–0.1136	–0.0444

Notes: The dependent variable is short-term debt over total assets. The main regressors are firm size, measured by log(TA_{it}) in columns (1)-(6) and log(EMP_{it}) in columns (7)-(12); AGE_{it} (firm age); $COLLAT_{it}$ (tangible fixed assets over total assets); $PROFIT_{it}$ (net income over total assets); RG_{it} (DHS revenue growth); and additionally CTA_{it} (cash over total assets) in columns (7)-(12). All regressions include both industry×year and county×year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 1. SEs are clustered at the industry and year level.