# Leverage over the Life Cycle and Implications for Firm Growth and Shock Responsiveness*

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**Abstract**

We study the leverage of U.S. firms over their life-cycle and implications for firm growth and responses to shocks. We use a new dataset that matches private firms' balance sheets to U.S. Census Bureau's Longitudinal Business Database (LBD) for the period 2005–2012. A number of stylized facts emerge. First, firm size and leverage are strongly positively correlated for private firms, both in the cross section of firms and over time for a given firm. For public firms, there is a weak negative relation between leverage and size. Second, young private firms borrow more, but firm age has no relation to public firms' leverage. Third, while private firms switch from debt to equity financing as they age, public firms slightly reduce equity financing as they age. Building on this "normal times" benchmark and using the "Great Recession" as a shock to financial conditions, we show that, for private firms, firm size can serve as a good predictor of financial constraints. During the Great Recession, leverage declines for private firms, but not for public firms. We also provide evidence that private firms' growth is positively related to leverage, as they finance their growth during normal times with short-term borrowing, whereas the relationship between leverage and firm growth is negative for public firms. These results suggest that public firms are not financially constrained during normal times or during crisis, but private firms are.

Keywords: Leverage, census data, firm life-cycle, financial constraints, age, short-term debt

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# 1 Introduction

There is an extensive literature studying the growth and employment dynamics of the U.S. firms over their life-cycle. Far less is known about how these firms finance their growth. Much of what is known about firms' financing behavior derives from publicly-listed, relatively large and old firms in Compustat. Yet, the behavior of private firms, which are much younger and smaller on average, has important macroeconomic implications since these firms account over 70 percent of aggregate US employment and over 55 percent of aggregate US gross output, and they are the ones that are most susceptible to the effects of financial shocks that impede lending and borrowing.[1]

Our aim in this paper is to better understand how firms at different points in their life-cycle choose to (or are able to) finance their operations and the implications of this life-cycle financing on firm growth and responsiveness to aggregate shocks. We construct a new data set on firm financing over the life-cycle using balance sheets of both publicly-traded and privately-held firms matched to the U.S. Census Bureau's Longitudinal Business Database (LBD). We refer to our new data set as LOCUS, that combines LBD, "L", with balance sheet data of privately-held firms from Bureau van Dijk's Orbis, "O", and publicly-listed firms from Standard & Poor's Compustat, "C", for the United States, "US". Our new data set, LOCUS, allows us to compare the relatively understudied behavior of leverage for private firms with that of the large listed firms, which has been the main focus of the existing literature. We explore leverage both in cross-section and over time, as a function of the life-cycle dynamics of firms – proxied by their age and size. Once we establish these patterns, we focus on the implications of firms' financing on their growth and their response to shocks, particularly to the financial crisis of 2007–2008.

The firm dynamics literature has established that, conditional on age, firm growth is negatively related to the size of the firm. It is also the case that conditional on size, firm growth is negatively related to the age of the firm (e.g. Davis, Haltiwanger and Schuh (1996)). Benchmark models of firm growth, such as Jovanovic (1982) and Hopenhayn (1982), cannot account

[1] As we show in detail in our data section below, between 2005 and 2012, listed, non-financial firms accounted for around 25 percent of domestic employment and 46 percent of domestic gross output in the U.S. Using financial data for private non-financial firms in the United Kingdom, Zeltin-Jones and Shourideh (2016) documents that private firms finance nearly 80 percent of their investment using financial markets compared to only 20 percent among listed firms, and private firms disproportionately account for the transmission of financial shocks to the economy.

for these *conditional* dependencies. In such models, firms of the same age experience the same growth rate independently of their size. Cooley and Quadrini (2001) show that adding financial frictions to these models in the form of costly default and equity issuance can account for these life-cycle dynamics, since financial frictions cause firm size to depend not only on firm's productivity but also on equity. Albuquerque and Hopenhayn (2004) can also account for the firm dynamics observed in the data, though in their model financial frictions arise due to imperfect enforceability.

We can test main predictions of these firm dynamics models with financial frictions using our new U.S. firm-level data, LOCUS. This exercise will lead to two main contributions that are relevant for the literatures both on firm dynamics and financial frictions. First, despite having plausible theoretical mechanisms for generating realistic firm dynamics, there is very little evidence on the role of financial frictions in these dynamics. Second, models of financial frictions have very different predictions on how firms of different ages and sizes will borrow, and why. For example, the models of Cooley and Quadrini (2001) and Albuquerque and Hopenhayn (2004) predict different relationships between firm size and leverage. The former model implies that smaller, younger and more productive firms have higher leverage, and leverage declines over time as firms increase their equity. Hence, size and leverage are negatively associated conditional on age and productivity. In contrast, Albuquerque and Hopenhayn (2004) implies that larger and more productive firms have larger projects financed with long-term debt. Over time as firms' equity grow, firms pay down their long-term debt, which relaxes the borrowing constraint on the short-term debt. Therefore, as firms grow, they incur more short-term debt, leading to a positive relation between firm size and leverage based on short term debt. Total leverage (sum of short-term and long-term debt) and size might still be negatively related. Both of these models also predict a negative relation between age and leverage since young firms borrow more. There are other models of financial frictions such as Buera and Moll (2015) that assume that firms operate a constant returns technology and hence all firms have the same borrowing limit, and there is no heterogeneity in firm leverage by firm age and size.

Our results show extensive heterogeneity in leverage by firm age and size among private firms.[2] In the cross section of private firms, larger firms are more leveraged regardless of the maturity of the debt and they have less equity as a fraction of their assets. Over time, as private

[2] The relationships between leverage and size (or age) are conditional on all other firm-level observables that can influence leverage, which we control for in our analysis.

firms get older, their leverage decreases, both in terms of short-term and long-term debt, and their equity increases as a fraction of assets. Small private firms are the least leveraged, but young private firms are the most leveraged, indicating that size and age have different relationships with leverage for private firms. The negative relationship between age and leverage is most likely driven by firms starting out at a size that is below their efficient scale, and so new firms choose to borrow more than older firms.

For public firms, the relationship between short-term leverage and size is weak and slightly negative. In contrast, very large public firms have high leverage in terms of long-term debt. This compositional effect results in no robust relation between total leverage and size for public firms. At the same time, equity-size relationship has an inverted U-shape for public firms. Since these firms have access to external equity via stock issuances, they issue less external equity and turn toward long-term debt borrowing as they become larger. Compared to private firms, the relationship between age and leverage is far weaker among public firms for all measures of leverage. Public firms appear to slightly reduce their equity as they age, which is consistent with them being leveraged in long term debt as they grow older and become larger.

What do these result imply for firm growth and response to aggregate shocks? Borrowing constraints of firms play a critical role in macroeconomic analyses when there are financial frictions. In the models such as Holmstrom and Tirole (1997), cash flows determine the constraint, whereas the liquidation value of physical assets that firms can pledge as collateral is important in models such as Hart and Moore (1994); Schliefer and Vishny (1992); Bernanke and Gilchrist (1999), Kiyotaki and Moore (1997), Mendoza (2010), Jermann and Quadrini (2012), Moll (2014), Buera and Moll (2015), Evans and Jovanovic (1989), Brunnermeier and Sannikov (2014).[3] No matter how the borrowing constraint is determined, this literature typically abstracts from firm heterogeneity and firm dynamics to mainly focus on short-term borrowing behavior represented by a one-period borrowing constraint that limits the amount a representative firm can borrow to some linear function of its assets. The constraint can also include the aggregate price of capital as in Bernanke and Gertler (1989), Virgiliu and Xu (2014).

At the same time, a large body of work in macro and corporate finance literatures seeks to understand the effect of firm heterogeneity on sales, investment, and employment responses of firms to aggregate shocks, where these shocks lead to tightening of credit such as finan-

[3] Lian and Ma (2015) show that, in a sample of listed firms, large firms' constraints are determined by cash flows, whereas small firms are more dependent on asset values.

cial crises or contractionary monetary policy. Models such as Cooley, Marimon and Quadrini (2004), Khan and Thomas (2013), Gopinath, Kalemli-Ozcan, Karabarbounis and Villegas-Sanchez (2017), Quadrini (2000), Cagetti and De Nardi (2006), Dinlersoz, Hyatt and Janicki (2017) put firm heterogeneity at the heart of financial constraints. These constraints play an important role in the propagation of aggregate shocks. The seminal work by Gertler and Gilchrist (1994), shows that adverse shocks are propagated via small firms' constraints in access to capital markets; that is, the financial accelerator mechanism works via credit constraints for small firms.

The empirical literature is divided on the role of heterogeneity in the transmission of monetary policy. While there are many empirical papers using data on listed firms from Compustat that show a higher sensitivity of small firms to credit tightening measured as recessions or monetary policy tightening (e.g. Farre-Mensa and Ljungqvist (2016), Rajan and Zingales (1995), Whited and Wu (2006)), there are others that use confidential data on select private firms from QFR database of Census Bureau and show that large firms respond more in terms of sales, inventories, short-term debt and employment (e.g. Kudlyak and Sanchez (2017), Chari, Christiano and Kehoe (2013)).[4] Even if small firms are more sensitive to shocks, the difference is not meaningful economically and also cannot be explained by financial frictions as shown by Crouzet and Mehrotra (2017). Using aggregate public data from the U.S. Census Bureau's Business Dynamics Statistics (BDS), Moscarini and Postel-Vinay (2012) also find that in the previous recessions, large firms suffered more than small firms in terms of employment; a finding confirmed by Kudlyak and Sanchez (2017) for the Great Recession. Fort, Haltiwanger, Jarmin and Miranda (2013) argue that this literature fails to separate the role of age and size.[5] In particular, QFR does not contain measures of firms' age, whereas Compustat does not include age and it measures employment using a firm's global operations, not just the U.S. domestic employment. LBD and BDS databases of the Census Bureau, instead, provide both domestic employment and age measures for all private and public firms in the U.S. This coverage is key since different shocks (financial versus demand) and different cyclical episodes (monetary policy changes versus unemployment spells) might affect the response of small and large firms differentially conditional on their age. Using BDS and focusing on a longer time span, Fort et al. (2013) find that young/small business are more sensitive to businesses cycle shocks.

[4]The latter paper shows that greater sensitivity of small firms is not robust to all time periods and in most recessions since 1950s the response of small and large firms were similar.

[5]For instance, Moscarini and Postel-Vinay (2012) does not condition on age.

It has also proven difficult to map firm size to financial constraints via variables on actual borrowing such as leverage, short-term debt and liquid assets. Crouzet and Mehrotra (2017) shows that there is no difference by firm size in the behavior of short-term debt and bank debt as a response to business cycles. On the other hand, matching listed firms from Compustat to their establishments in LBD data, Giroud and Mueller (2017) show that firm leverage is important in propagation and when house prices dropped employment fell significantly more in establishments belonging to more leveraged listed firms. Jeenas (2018), using listed firms from Compustat, shows that highly leveraged firms are *more* responsive to monetary policy shocks in terms of investment, since they decrease investment more after a monetary policy contraction. Using Compustat data and similar high frequency identification of monetary policy shocks, Ottonello and Winberry (2018) find exact opposite result that highly leveraged firms are *less* responsive to monetary policy shocks, that is, after a monetary policy contraction, these firms invest more. Papers that identify credit supply shocks directly show that small and young firms are affected more by such shocks (e.g. Chodorow-Reich (2014), Chodorow-Reich and Falato (2017), Gilchrist, Siemer and Zakrajsek (2018).)

We argue that in order to identify the link between firm size, leverage and financial constraints, three ingredients are key: First, one has to condition on age. Second, the dataset has to encompass full size distribution covering the range of small firms, and third, size should be measured with employment. We believe, most of the previous findings in the literature reflect differences in the growth and financing policies of firms at different stages of firms' lifecycles. Firms' need for internal versus external finance will vary with their lifecycle and firms which use external finance will be more susceptible to credit shocks. In that sense, large firms, by having a greater access to credit, might be more negatively impacted during periods of credit crunch. On the other hand, very large firms can also substitute between bank and market debt. Similarly, very small firms might have limited access to credit during both normal times and crisis times and hence hard to identify the effect of shocks on such firms. As a result, higher leverage in terms of short-term debt may not be mapped directly to being financially constrained and thus coverage of both small and large firms is essential.[6] Our finding

[6]Kalemli-Ozcan, Laeven and Moreno (2018), using ORBIS data for private firms for several European countries, show that firms who entered the crisis with higher leverage in 2009, decreased their investment more in the aftermath of the crisis. They also show that larger firms, who invest less during normal times, invested more during the crisis time. This result supports the conjecture that highly leveraged firms become financially constrained during the crisis when the credit conditions tighten. Not all *large firms* are highly leveraged and this allows to identify different roles for leverage and size in determining investment, where both large and low leveraged

that short-term leverage ratios are higher in larger "private" firms but lower in larger "public firms" supports this line of argument. And finally, employment is a better measure of size than assets. Most papers measure size with assets and typical small firm measure of 25th-30th percentile in sales or assets will correspond to firms with assets less than 1 billion, which is not small. In addition depending on whether assets are measured at book value or at market value, a size measure based on assets will fluctuate more (or less) than a size measure based on employment even though the firm is actually not growing or shrinking.

In models of financial frictions, firms sometimes do not borrow because they operate at an efficient scale, and sometimes because they are unable to access credit. Our finding that leverage ratios are higher in larger firms may be driven by larger firms having better and larger projects to finance, and therefore demand more credit, or lenders may be more willing to lend to larger firms and hence small firms are credit constrained. We argue that size being an important correlate of leverage for private firms is at least in part driven by credit constraints that differentially affect small firms. To test this implication, we use the "Great Recession" as a shock to financial conditions, which can make financial frictions matter more for already constrained firms and also for firms who become constrained when credit conditions tighten. In fact, this is exactly what we find. For private firms, it is not only that small firms have even lower leverage, but also larger private firms are affected from the crisis and decrease their borrowing relative to their assets. Short-term leverage is more strongly associated with size in the pre-crisis period than during the crisis period, i.e. the size differential contracts during the crisis. This finding is similar to the papers that find that larger firms respond more to the episodes of credit tightening. Our results suggest that some firms might be credit constrained both in normal and crisis times (small private firms) and some firms might become more constrained during the crisis times (large private firms) and some firms are never appear to be constrained (large public firms).[7]

Our results condition on standard determinants of leverage such as collateral/tangibility and sector-year fixed effects and firm-level profitability in order to account for sector and firm level demand shocks, which allow us to interpret the variations in actual amount of borrowing stemming mostly from variations in the maximum amount firms can borrow (financial con-

firms invest more when credit frictions tighten.

[7]Using financial data from the universe of firms in Canada, Huynh, Paligorova and Petrunia (2018) obtain results that are similar to our results from the U.S. They find that private firms have more leverage than public firms, driven by the fact that private firms rely more on short-term debt compared to public firms.

straints), where this amount changes across firms of different sizes and ages. In other words, our underlying assumption is that, conditional on observables that can affect demand for borrowing, for a given firm size (or age) level there are enough financially constrained firms that the average leverage of firms reflects the underlying borrowing constraint for that level. We also condition on labor productivity as an additional proxy for growth potential and underlying productivity of firms. The estimates on firms' productivity further supports our access to finance/financial frictions interpretation, since more productive firms, conditional on age and size, have higher short-term leverage as predicted, but only if these firms are private firms. There is no relation between productivity and short-term leverage for public firms. Productive public firms have higher leverage based on long-term debt, whereas the relationship between productivity and long-term leverage is insignificant for private firms. These results suggest that smaller private firms have more difficulty accessing long-term financing, even if they are productive. The firm fixed effect panel specification that uses "within" variation show the robust relationship between firm size and short-term leverage, further supporting our interpretation. This result is noteworthy since in general the literature using listed firms find very persistent patterns in leverage, where firm fixed effects specifications lead to insignificant connection between leverage and its determinants, collateral, profitability and size (e.g. Lemmon, Roberts and Zender (2008).)

Our results in terms of firm growth are as follows. We show that leverage and firm growth are strongly positively correlated for private firms in the cross section both during normal times and during the crisis. In the firm fixed effect panel specifications, this positive result weakens during the crisis, which suggests that financial constraints might become more binding for a larger set of private firms during the crisis. If these firms finance their growth with leverage during normal times and cannot borrow as much during crisis times, then the relation between growth and leverage should become weaker, when we identify this relation from within firm variation. By contrast, public firms' growth is negatively related to their short-term leverage in normal times and this relation is not affected by the crisis. This result is consistent with public firms not being financially constrained, but rather slow-growing large public firms being leveraged. In addition, size has no differential affect on firm growth during crisis only when we control for short-term leverage, which suggest that size is a good predictor of financial constraints that is captured by short-term leverage.

We proceed as follows. Section 2 reviews the literature. Section 3 describes the data and presents detailed statistics on the share of aggregate US economic activity accounted by listed firms. Section 4 describes the empirical methodology and results. Section 5 concludes.

## 2 Literature

In this section, we provide a brief survey of the literatures that our paper relates to. We start with the literature on firm borrowing and financial constraints and its implications on how firm age and firm size may be related to both the borrowing behavior and the financial constraints firms face.

A large number of studies have proposed models in which agents borrow in order to finance projects. Contributions such as Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) introduce financial frictions into standard macroeconomic models and demonstrate that financial frictions have substantial ability to amplify business cycle fluctuations.[8] In most models, the borrowing constraint takes the generic form

$$b_t \leq \theta k_t \tag{1}$$

where $t$ denotes time, $b_t$ is debt, $k_t$ is capital (or assets) and $\theta$ is a constant that limits debt to a fraction of assets. Capital can be a function of aggregate prices (e.g. $k_t(P_t)$), in order to generate the financial accelerator mechanism via valuation of assets. Another version of this constraint may include interest rate, $R_t$. In that case the constraint can be written as

$$R_t b_t \leq \theta k_t \tag{2}$$

Most of these models abstract from entry, firm growth and exit, and make no predictions about the relationship between borrowing and firm age. Other contributions in the macro literature, such as Mendoza (2010) and Jermann and Quadrini (2012), employ representative agent models and do not make cross-sectional predictions about the relationship between size and borrowing behavior. In such models, the borrowing constraint binds, $b_t = \theta k_t$. Clearly, this class of models will imply constant leverage in the cross-section of firms. Given the firm-

[8] Kiyotaki and Moore (1997) propose an extension of their representative agent framework in which only some firms have investment opportunities in any given period while those firms without investment opportunities will pay down their debts. This extension of their model therefore might predict a positive relationship between borrowing and size.

level heterogeneity in the data, we explore a model in which there is such heterogeneity.

There is a set of models that introduce heterogeneity in productivity among firms. This heterogeneity leads to a firm size distribution. However, when firms operate constant returns to scale technologies, firms borrow as much as they can up to a borrowing constraint. This is the case in models such as Moll (2014) and Buera and Moll (2015), where firms always borrow as much as they can, implying that the ratio of borrowing to total assets, and hence leverage, does not vary among active firms, and the leverage is the same for firms of different sizes. Hence, it is not possible to obtain predictions about differences in cross-sectional financial frictions relating to firm size and firm leverage.

Richer predictions on how borrowing behavior may be related to firm size and firm age come from the smaller set of studies in which firms operate decreasing returns to scale technologies. For instance, Cooley and Quadrini (2001), Khan and Thomas (2013), and Crouzet and Mehrotra (2017) introduce financial frictions into models of industry dynamics. A decreasing returns to scale technology is also a common modeling choice in the entrepreneurship and occupational choice literature as in Cagetti and De Nardi (2006), Buera and Shin (2013), Bassetto, Cagetti and De Nardi (2015), and Dinlersoz et al. (2017).[9] In most of these models, the borrowing constraint a firm faces is specified again as a short term (one-period) constraint, where borrowing is limited to some multiple of the entrepreneur's current capital or assets. The multiple can be a constant (e.g. Evans and Jovanovic (1989), Quadrini (2000), Cagetti and De Nardi (2006)), as in the above equations, or a more general function of the firm's productivity or capital stock (e.g. Virgiliu and Xu (2014), Khan and Thomas (2013)).[10]

These models generally imply that entrepreneurs with more productive (larger) projects take out larger loans than those with less productive (smaller) ones, and with predictions about borrowing behavior by firms as they age and grow.[11] Decreasing returns to scale implies that

[9] While some models assume all firms employ a decreasing returns to scale technology, models such as Cagetti and De Nardi (2006), Bassetto et al. (2015), and Dinlersoz et al. (2017) distinguish between an entrepreneurial sector in which firms are operated by households using a decreasing returns to scale technology, and a corporate sector which is characterized by a constant returns to scale technology. In these models, financial constraints apply only to the entrepreneurial sector.

[10] In Gopinath et al. (2017), although firms operate under CRS, the limit on borrowing is a convex function of firm's capital, implying that the constraint on borrowing relaxes as a firm grows, but at a decreasing rate. This models also implies larger firms are more leveraged.

[11] In some of these models, there is an important distinction between the predictions on firm size unconditionally, and conditional on age. Because all firms start out small, the set of large firms contains many that have paid off their debts. Hence, borrowing declines in firm size in Figure 3 of Cooley and Quadrini (2001) (page 1296). But conditional on age, firms that borrow more are those that experience better productivity shocks.

firms have an optimal size, and as firms approach this size, the incentive to borrow and the amount borrowed as a fraction of firm's assets naturally lessens. A natural prediction of these models is that firm leverage should be decreasing in age.[12]

Models in which entrepreneurs operate such decreasing returns to scale technologies make more ambiguous predictions about how borrowing will vary by firm size, which also vary with specific modeling choices. In most such models, businesses with better ideas will want to borrow more than those with worse ideas. In most cases, this leads to larger businesses having more leverage, at least very soon after entry. Indeed, Hurst and Lusardi (2004) argue that the vast majority of entrepreneurs do not require a large loan to operate their businesses at an efficient scale and so are not credit constrained. Cagetti and De Nardi (2006) reconcile this finding with this class of models via a calibration in which only the largest businesses are affected by credit constraints because most business owners provide all needed finance. The longer term differential depends on the speed of debt repayment. However, this size-leverage depends on the way that financial frictions are modeled. In Cooley and Quadrini (2001) financial frictions are modeled via default risk that is priced with an interest rate differential rather than a borrowing limit. Financial intermediaries share the costs of default, which in turn induces smaller, riskier businesses of any age to borrow more. However, when financial intermediaries choose the size of loans (i.e., have a borrowing limit that is endogenously determined) as in Albuquerque and Hopenhayn (2004), more productive businesses may be allowed a higher leverage ratio than smaller ones since they are further away from the exit threshold.

A smaller number of studies on financial frictions endogeneize borrowing and distinguish between short term and long term debt, including Diamond (1991), Albuquerque and Hopenhayn (2004), and Alfaro, Bloom and Lin (2016). The model in Albuquerque and Hopenhayn (2004) features firm dynamics that is driven by a sequence of revenue shocks over time, which generates predictions regarding borrowing behavior and constraints by firm size and age over the life-cycle of firms. A firm needs to raise an initial amount of capital to start operation, and may also need to borrow in subsequent periods to finance production. Rather than being exogenously given, borrowing constraints naturally arise due to the limited enforcement of contract between the firm and the lender, and the resulting incentives – the lender does not

[12] A similar approach is taken by Clementi and Hopenhayn (2006). In their framework like many others with a concave production technology, firms start with a large initial investment pay down their debts over time. However, heterogeneity among firms is beyond the scope of their study and so does not offer predictions of borrowing where size is conditional on age.

necessarily provide all the startup capital to the firm in order to prevent the entrepreneur from running away with some of that capital. Importantly, the model distinguishes between short term and long term debt, which are both endogenously determined and related to each other. As a firm grows, it builds equity, and gradually pays down its debt. The higher a firm's long term debt, the less capital it is able to borrow for current production, resulting in a negative relationship between long term and short term debt. Firms therefore aim to pay their long term debt as quickly as possible to render short term borrowing constraint non-binding.

The Albuquerque and Hopenhayn (2004) model has several predictions on the firm life-cycle dynamics of debt.[13] Firms with prospects of better revenue (productivity) shocks and growth opportunities are associated with more debt initially, exhibit lower failure rates, pay off their long-term debt faster, and eliminate their short-term borrowing constraint quicker. At any point in time, larger firms have more leverage and long-term debt, conditional on the revenue shock. As the equity of an entrepreneur grows, debt maturity also changes: short-term debt increases relative to the long-term debt. In general, short term borrowing constraints relax as a firm grows, and firms can eventually become non-dependent on external financing as they continue to pay off long term debt and the accumulated equity becomes sufficient to finance the firm. Therefore, conditional on the size of the firm, older firms have lower debt.

Most models in this literature impose a short-term borrowing constraint represented by a one-period limit on how much a firm can borrow to finance production. The predictions from models that feature firms with a constant returns to scale technology and a borrowing limit that is independent of firm size are rather stark and suggest that firm borrowing behavior should be independent of firm size.

Our paper is also related to a large literature that tries to understand the determinants of listed firms' balance sheet structure and its effects on investment and hiring decisions. The seminal work of Rajan and Zingales (1995), using data on non-financial publicly listed firms in G-7 countries in late 1980s, document that size, profitability, and collateral are the most important determinants of leverage of firms. More recently, Custodio, Ferreira and Laureano

[13]Here, we note the model's general predictions. Albuquerque and Hopenhayn (2004) also specify a special case in which lenders coordinate on both the availability of credit as well as the borrowing limit, in which case overall debt can be written as a sequence of short-term contracts, and the model exhibits dynamics of total debt in which the borrowing constraint can be characterized by Equation 1, where $\theta$ is a function of prior borrowing, and the firm's productivity draw. But in their more general case, a firm's level of long-term debt is given by an incentive compatible sequence of repayments that solve a recursively defined default problem, and only short-term debt is characterized as in Equation 1.

(2012) document a rising reliance on short-term debt among U.S. listed firms, particularly driven by small firms who face higher information asymmetry and choose to issue more public equity. Ajello (2016) finds that between 1989 and 2008, thirty-five percent of U.S. listed firms' investment is funded using financial markets. Similar to Ajello (2016), Covas and Den Haan (2012) show listed firms finance investment with both debt and equity, and that both forms of financing are more pro-cyclical for smaller listed firms. Begenau and Salomao (2015) find that while large firms are able to substitute between debt and equity over the business cycle, small firms' debt and equity are both procyclical.

# 3 Data

We argue that a new database is needed that covers the financial accounts of private firms since listed firms in the U.S., account a small of portion of the economic activity. Between 2000 and 2013, around 6,600 firms were actively publicly traded annually, which accounts for a mere 0.13 percent of all firms in the economy.[14] Less clear is the fraction of employment and revenue that these firms account for. This section attempts to shed light on this topic by relying primarily on publicly-available data.

Total U.S. employment is obtained from the Census Bureau's Business Dynamic Statistics (BDS). The BDS is derived from the LBD and covers 98 percent of private employment. Data are available annually and can be broken down by firm size, age, location, and sector. This section uses the economy wide and sector tables. The total employment reported in the economy wide table is used to calculate the contribution of listed firms to total U.S. employment. The sector table includes 9 broad sectors – agriculture, forestry, and fishing (AGR); mining (MIN); construction (CON); manufacturing (MAN); transportation, communication and public utilities (TCU); wholesale trade (WHO); retail trade (RET); finance, insurance, and real estate (FIRE); and services (SRV). This table is used to calculate the contribution of non-FIRE

[14] The 6,600 figure is arrived at by beginning with Compustat and 1) keeping one observation per (gvkey, year) pair; 2) keeping (gvkey, year) pairs with a positive security price in the indicated year or in the years that bracket the indicated year, as in Davis, Haltiwanger, Jarmin and Miranda (2006); 3) dropping financial instruments (ETFs, ADRs, etc), which involves dropping observations with missing NAICS codes and those with NAICS equal to 525; 4) dropping non-U.S. firms, which involves dropping observations with simultaneously missing EIN and state information or those with simultaneously missing EIN and a non-U.S. address; and 5) dropping firms in public administration (NAICS code 92). The 0.13 percent figure is arrived at by dividing 6,600 by 5,020,309, which is the average number of firms in the U.S. economy between 2000 and 2013 derived from the Census Bureau's Business Dynamic Statistics data.

listed firms to total non-FIRE U.S. employment by taking the total employment reported in the economy-wide table and subtracting from it employment in FIRE reported in the sector table. The second statistic is reported because this paper focuses on the non-financial sector.[15]

Total U.S. gross output is obtained from the Bureau of Economic Analysis' Industry Economic Accounts. Gross output measures sales, including those to both final users and other industries and is measured in current prices.[16] Total gross output by private industries is used in calculating the contribution of listed firms to total U.S. gross output. Total gross output by private industries net of the finance, insurance, real estate, rental and leasing sectors (FIRE) is used in calculate the contribution of non-FIRE listed firms to total non-FIRE U.S. gross output.

Calculating the contribution of listed firms to U.S. employment and gross output is not straightforward for two reasons. First, not all firms in Compustat are actively traded. Following Davis et al. (2006), this paper defines active listed firms as those with a positive security price in a particular year or in the years that bracket that year. Second, and more importantly, 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 in the concepts give rise to discrepancies between the LBD and Compustat reported employment and revenue. Similar to Davis et al. (2006), this paper compares the LBD and Compustat employment and revenue of matched firms. Between 2007 and 2013, LBD employment is only 75 percent of Compustat employment and LBD revenue is only 79 percent of Compustat revenue. It is therefore important to adjust the employment and revenue reported in Compustat when calculating the contribution of listed firms to the U.S. economy because the BDS measures only domestic employment and the BEA measures only domestic gross output.

To highlight the importance of taking into consideration these two factors, this paper reports several alternative measures of listed firms' contribution to the U.S. economy:

1. The first version (labeled "raw" in the figures) sums Compustat reported employment (variable emp) and revenue (variable revt) across all listed firms and divides it by total

[15] This paper excludes only the finance and insurance sectors (NAICS code 52). The BDS groups finance and insurance (NAICS 52) with real estate, rental and leasing (NAICS 53). As a result, when calculating the contribution listed firms to employment and revenue in non-financial sectors, this section excludes FIRE (NAICS codes 52 and 53) from data informing both the numerator (Compustat) and denominator (BDS and BEA).

[16] Given the BEA definition of gross output, this measure corresponds to the revenue variable observed in Compustat. While the BEA provides data on gross output, other sources such as the BLS do not include this variable.

BDS employment and BEA gross output.[17]

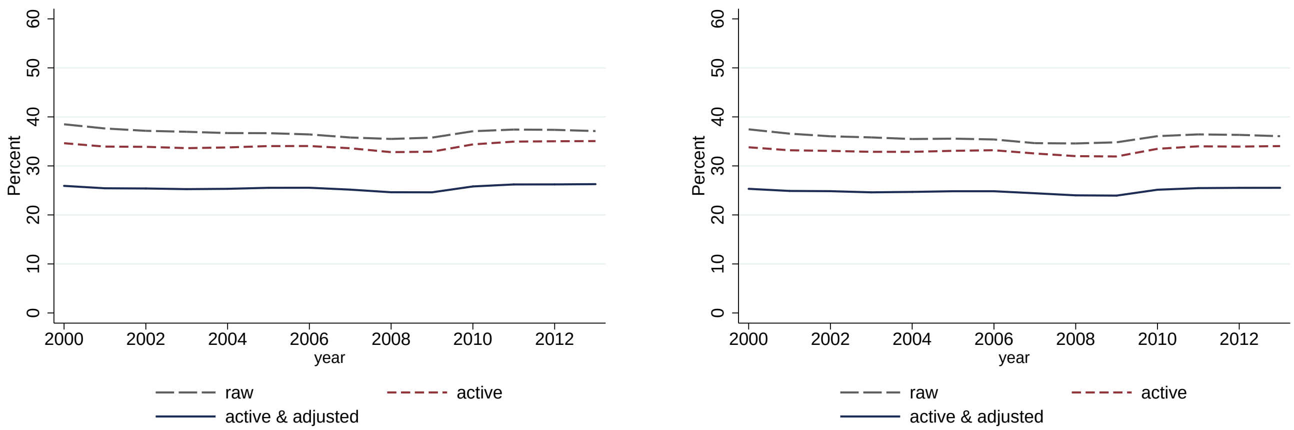
2. The second version (labeled ”active” in the figures) sums Compustat reported employment and revenue across all actively traded listed firms and divides it by total BDS employment and BEA gross output.

3. The third version (labeled ”active & adjusted” in the figures) sums Compustat sums adjusted (by a factor 0.75) employment and adjusted (by a factor 0.79) revenue across all actively traded listed firms and divides it by total BDS employment and BEA gross output.

Figure 1 reports the contribution of listed firms to private sector employment. The left panel depicts the contribution of listed firms to total private sector employment and the right panel depicts the contribution of non-FIRE listed firms to non-FIRE private sector employment. Note first that in both the left and right panels the contribution has remained quite stable over the entire period 2000-2013. In the left panel, Compustat firms appear to account for around 37% of private sector employment on average when no adjustments are made for active trading and foreign employment. This average falls to 34% if only actively-traded firms are considered and falls further still to 26% when the domestic employment of actively traded firms is considered. The right panel focuses on the non-FIRE private sector and here non-FIRE, actively traded listed firms account for around 25% of annual non-FIRE private sector employment.

[17] The listed firms that are included are obtained by starting with Compustat and 1) keeping one observation per (gvkey, year); 2) dropping financial instruments (ETFs, ADRs, etc)which involves dropping observations with missing NAICS codes and those with NAICS equal to 525; 3) dropping non-U.S. firms, which involves dropping observations with simultaneously missing EIN and state information and those with simultaneously missing EIN and a non-U.S. address; and 5) dropping firms in public administration (NAICS code 92).

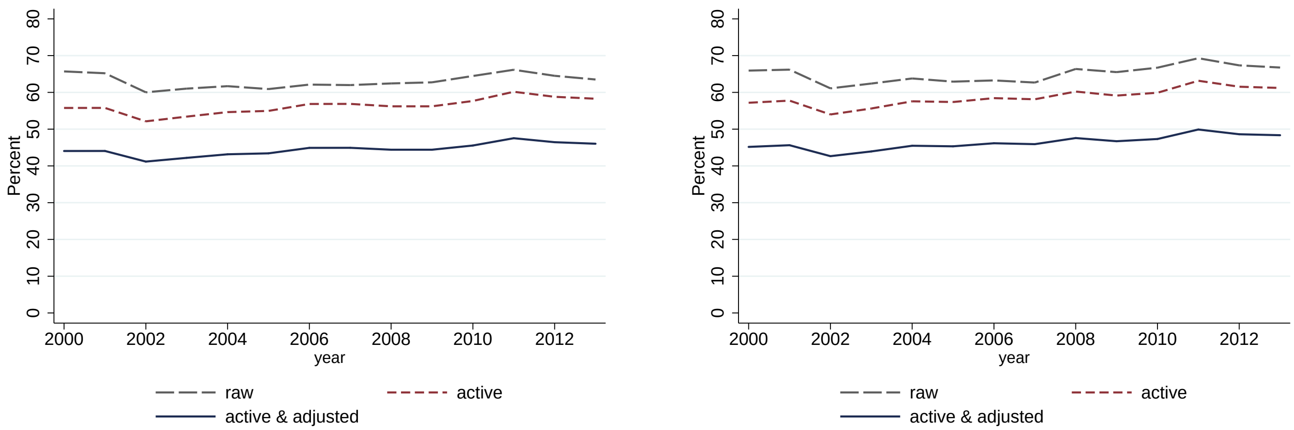
Figure 1: Employment: % of Private Sector (left) and non-FIRE (right)




**Notes:** The left figure plots the contribution of listed firms to private sector employment. The right figure plots the contribution of non-FIRE listed firms to non-FIRE private sector employment. Listed firm employment is obtained from Compustat (revt variable) and private sector employment is obtained from the Census Bureau's BDS tables. In each figure the dashed grey line depicts the raw Compustat employment for listed firms over BDS employment; the dashed red line depicts the raw Compustat employment for actively traded listed firms over BDS employment; and the solid blue line depicts the adjusted (by a factor of 0.75) Compustat employment for actively traded listed firms over gross BDS employment.

Figure 2 reports the contribution of listed firms to private sector gross output. The left panel depicts the contribution of listed firms to total private sector gross output and the right panel depicts the contribution of non-FIRE listed firms to non-FIRE private sector gross output. Similar to the employment contribution depicted in the previous figure, in both the left and right panels the contribution of listed firms is fairly stable over time. In the left panel, Compustat firms appear to account for around 63% of private sector gross output on average when no adjustments are made for active trading and foreign employment. This average falls to 56% if only actively-traded firms are considered and falls further still to 44% when the domestic gross output of actively traded firms is considered. The right panel focuses on the non-FIRE private sector and here non-FIRE, actively traded listed firms account for around 46% of annual non-FIRE private sector gross output. Both figures confirm that publicly-traded firms account for an important share of the U.S. economy, but that privately-held firms account for the majority of employment (74%) and gross output (56%).

Figure 2: Gross Output: % of Private Sector (left) and non-FIRE (right)




**Notes:** The left figure plots the contribution of listed firms to private sector gross output. The right figure plots the contribution of non-FIRE listed firms to non-FIRE private sector gross output. Listed firm gross output is obtained from Compustat (revt variable) and private sector gross output is obtained from the BEA's Industry Economic Accounts tables. In each figure the dashed grey line depicts the raw Compustat gross output for listed firms over BEA gross output; the dashed red line depicts the raw Compustat gross output for actively traded listed firms over BEA gross output; and the solid blue line depicts the adjusted (by a factor of 0.79) Compustat gross output for actively traded listed firms over gross BEA output.

The U.S. Census Bureau's LBD has comprehensive data on firm age, employment and, as of recently, revenue, for the entire universe of private firms, but lacks information on firm balance sheets.[18] Thus, to study the financing behavior of private firms in the U.S. and to verify predictions arising from the literature on financial frictions, we construct a new data set by matching LBD data to Orbis and Compustat using both national firm-level identifiers and an iterative probabilistic name and address matching procedure.[19] From the LBD we obtain information on firm employment, revenue, age, industry, and legal form. Our financial data on listed firms come from Compustat, and our financial data on private firms come from the Orbis database. Both sources contain detailed firm-level balance sheets, income statements, and profit and loss accounts. Orbis is compiled by Bureau van Dijk Electronic Publishing (BvD), a Moody's company. Firm-level administrative data is first collected by local Chambers of Commerce and the business register. The data are then relayed to BvD through 40 different information providers. Although private company reporting is voluntary in the U.S., we show

[18]While listed firms are legally required to disclose their financial statements, private firms are not. As a result, Compustat, which covers the universe of listed firms in the U.S., has been extensively relied upon in the literature to study firm financial structure and aggregate implications of financial frictions.

[19]Please refer to appendix B for additional details on the matching procedure.

that LOCUS covers more firms than other data sets provided by alternative private vendors.

Research on the financing behavior of private firms has thus far relied on two types of data. The first type includes SDC VentureXpert and CapitalIQ, which focus on private equity issuances and buyouts. As a result, they provide no information on bank debt, and only include the very small sample of firms that raise private equity.[20] The second type of data used to study private firms focuses on very small and very 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.[21] Similarly, the Kauffman Firm Survey (KFS) focuses on the experience of young firms. It tracks a single cohort of 5,000 firms born in 2004 through 2011.[22] All these data cover select set of private firms that are not representative of the US economy and not span the full firm age and size distributions.

Two exceptions that cover a larger set of private firms over time are the U.S. Census Bureau's Quarterly Financial Report (QFR) survey and Sageworks. The QFR covers the mining, manufacturing, wholesale trade, retail trade and select service sectors. Each quarter it surveys about 4,600 large corporations in these sectors, in addition to a select sample of approximately 5,000 small and medium sized firms in the manufacturing sector. It therefore contains detailed balance sheet information for several thousand private and listed firms across the age and size distributions in the manufacturing sector. Two features distinguish our data LOCUS from the QFR. First, LOCUS encompasses a large sample of small and large firms beyond just the manufacturing sector.[23] Second, the QFR can only be linked to the LBD in Census years to obtain firm employment and age information, which hinders annual analysis and a full assessment

[20] 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.

[21] The SSBF has been used to study borrower-lender relationships as in Petersen and Rajan (2002) and the capital structure decisions of single-owner corporations as in Ang, Cole and Lawson (2010) and Cole (2013). Using the 1993 survey, Berger and Udell (1998) show that due to a high degree of informational opacity, small businesses depend more on funding provided by insiders and receive external funding primarily from private equity and debt markets, as opposed to the public market. By linking loan-level data from the Small Business Administration with the LBD, which covers only very small firms, Brown and Earle (2017) shows that when local credit conditions are weak, access to SBA loans is associated with job growth.

[22] Robb and Robinson (2012) use the survey to document the importance of external financing, such as bank financing, for startups.

[23] Appendix A shows how the QFR coverage compares to the manufacturing sector in the LBD, Compustat and our LOCUS data using both revenue and total assets.

of the representativeness of the QFR sample as opposed to LOCUS data.

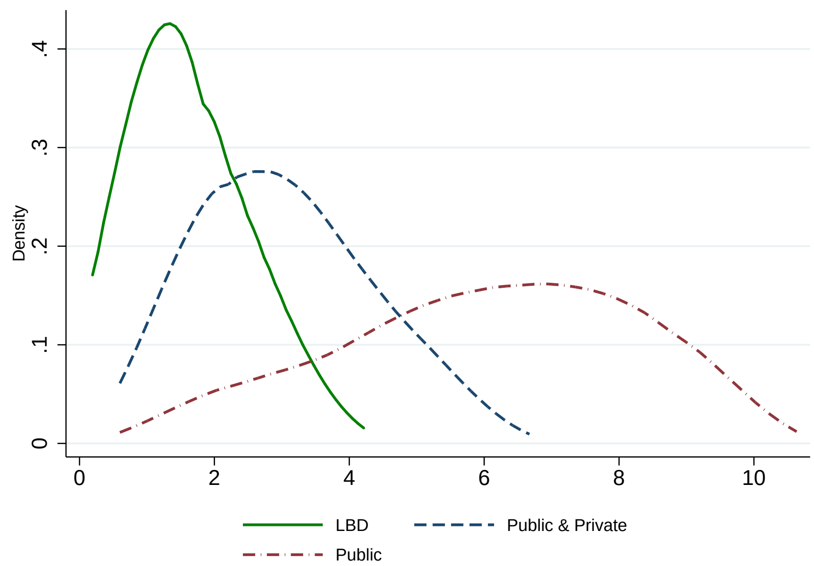
Another proprietary database, Sageworks, contains panel data on over 220,000 listed and private firms. Similar to LOCUS, Sageworks includes information from firm balance sheets and income statements, as well as industry classification and geographic location. In contrast to our LOCUS, Sageworks anonymizes firms (Asker, Farre-Mensa and Ljungqvist, 2015). This feature prevents matching the data to other sources, such as the LBD, that contain information on age and size (employment), both of which are thought to be theoretically and empirically crucial for the relationship between financial constraints and firm dynamics. Additionally, due to inability to match the data to census, a full assessment of how representative firms in the sample are relative of the whole U.S. economy cannot be performed.

To the best of our knowledge, the only other paper that uses ORBIS data for the U.S. is by Nikolov, Schmid and Steri (2017). However these authors do not match the ORBIS data to Census data. They show that private firms in ORBIS have higher leverage relative to the listed firms in Compustat, and are more profitable.

## 3.1 LOCUS Data

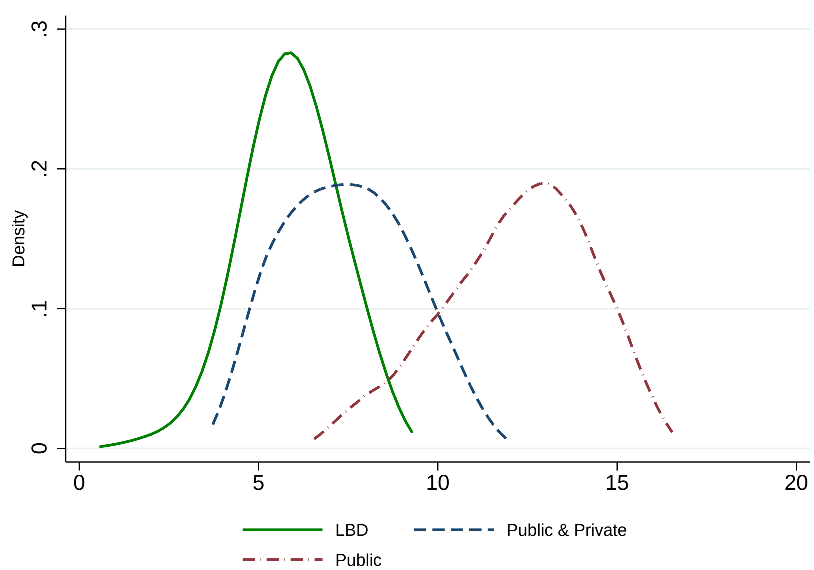
In all, our matched LBD-Orbis-Compustat data on U.S. firms (LOCUS) contains over 180,000 unique firms, 97 percent of which are privately held. Our matched sample covers around 31 percent of U.S. employment, 35 percent of payroll, and 38 percent of U.S. non-farm, non-financial revenue. Privately held firms in our sample consistently account for about 10 percent of the U.S. economy. What is perhaps most striking is how vastly different listed and private firms are. On average, listed firms in our sample have 34 times larger employment (6,200 employees versus 170 employees) and 64 times higher revenue ($293 million versus $7.7 million) than privately held firms in our sample.

Figure 3: Comparison of Employment Distributions: LBD, LOCUS & Compustat




**Notes:** This figure compares the distribution of firm-level employment, obtained from the LBD, among non-financial employer businesses in 2010 that are in LOCUS (contains both private and listed firms), Compustat (listed firms only), and LBD. The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements

Figure 4: Comparison of Revenue Distributions: LBD, LOCUS & Compustat




**Notes:** This figure compares the distribution of firm-level revenue, obtained from the revenue-enhanced LBD, among non-financial employer businesses in 2010 that are in LOCUS (contains both private and listed firms), Compustat (listed firms only), and LBD. The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements

Using employment from LBD and revenue from the revenue-enhanced LBD, figures 3 and 4 show that our LOCUS data vastly improve the coverage of small and medium sized firms both in terms of employment and revenue relative to the sample of listed (Compustat) firms on which the finance and macro-finance literatures are built. Figures 3 and 4 also illustrate that our LOCUS data is not representative of the whole U.S. economy. The average employment in LOCUS is 525 versus just 20 in the LBD; and the average age is 21 in LOCUS versus 11 in the LBD. Additionally, we determine that LOCUS firms have higher employment growth rates, are more likely to own multiple establishments, and are more likely to be nonprofits than firms in the LBD. This selection is driven by the fact that our sample contains only privately-held firms that report their financials. The non-representativeness of LOCUS is a concern because we believe that firm financing decisions are influenced by factors such as age, size, growth and legal form. If we naively run regressions using the raw, unweighted LOCUS data, we will misrepresent the strength of the relationship between leverage and firm characteristics such as age and size for the average firm in the economy 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 to the LBD, which contains private firms spanning the entire firm age and size distributions. To do so, we run a series of logistic regressions similar to Haltiwanger, Jarmin, Kulick and Miranda (2017) for private firms.[24] Our dependent variable is reporting status and is equal to one for the firm-year observations in LOCUS. To account for the possibility that selection into our matched data varies for firms continuing, entering and exiting the universe of employer-businesses, we estimate separate models for each of these categories. Our regressors are firm employment ($log(emp_i)$), age ($age_i$), indicator for firms 16 years or older ($D16_i$), employment growth rate ($EG_i$, 7 categories) for firm $i$, and a series of fixed effects for 3-digit NAICS industry ($ind$), multi-unit status ($mu$), and legal form ($lfo$, 3 categories).[25] The models we estimate in each year 2005 through 2012 for continuers, entrants and exiters are specified below:

1. **Employment continuers:**

$$R_{it} = \alpha + \gamma_1 log(emp_i) + \gamma_2 age_i + \gamma_3 D16_i + \gamma_4 EG_i + ind + mu + lfo + \varepsilon_i \quad (3)$$

[24]We exclude listed firms from the logistic regressions and assign them a weight of one in our subsequent analysis because they are required to report financials. As a result, LOCUS include all identifiable listed firms in the LBD.

[25]Legal form is divided into three categories – 1) corporation, 2) sole-proprietorship, partnership, and S-corporation, and 3) non-profits and other legal forms.

2. **Employment births:**

$$R_{it} = \alpha + \beta_1 ln(emp_i) + ind + mu + lfo + \varepsilon_i \tag{4}$$

3. **Deaths**

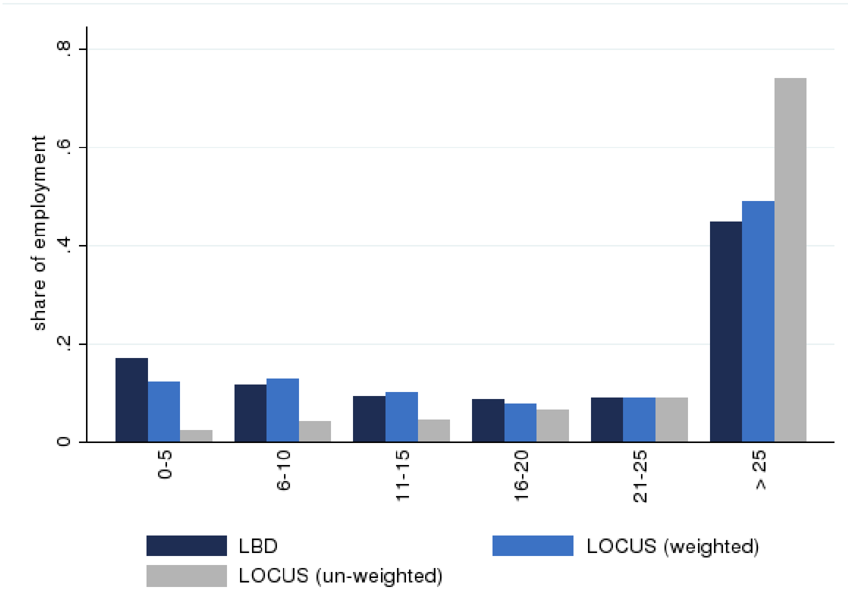
$$R_{it} = \alpha + \delta_1 log(emp_i) + \delta_2 age_i + \delta_3 D16_i + ind + mu + lfo + \varepsilon_i \tag{5}$$

We use the resulting predicted values to construct propensity scores, which we use as weights in the remainder of our analysis. As figures 5 through 7 and tables 1 and 2 show, this approach substantially decreases the observable differences between financial reporting and non-reporting privately-held firms once weights are applied.[26] Most noticeably, the weights reduce 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 we expect make different financing decisions than sole-proprietorships, partnerships and corporations.

In table 3, we compare the weighted means and standard deviations of key variables for the public and private firms in LOCUS. In constructing our analysis data, we winsorize all financial variables – collateral, profitability, equity over total assets and all leverage variables – at the 1st and 99th percentiles. Listed firms are 62 times larger than private ones and twice as old. Listed firms also are more profitable, and have higher collateral, total leverage and financial leverage. When we decompose leverage into short-term and long-term, private firms have higher short-term leverage, while public firms have higher long-term leverage. Private firms also have higher equity over total assets, could reflect their higher reliance on internal equity relative to listed firms.

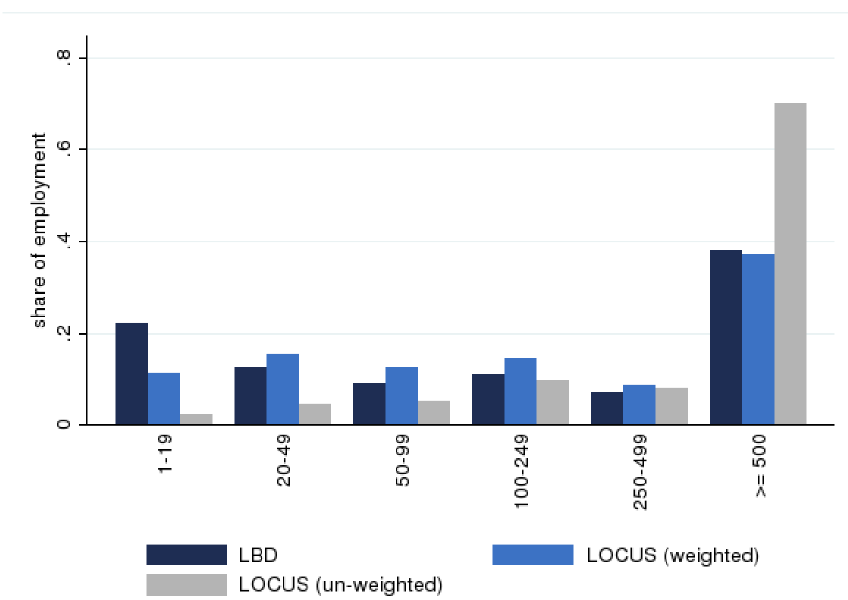
[26] In the figures the height of each bar and in the tables the share reported is the share of each sample employment accounted for by each group.

Figure 5: Comparison of Firm Age Distributions (% of emp)



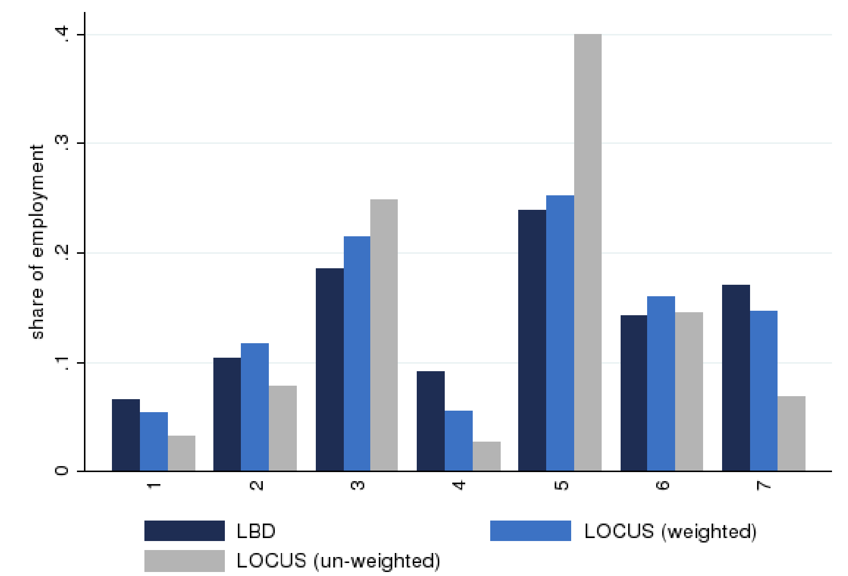

**Notes:** This figure compares the fraction of sample firm-level employment accounted for by each age group. Each bar represents a different sample. The first bar represents all private, non-financial employer businesses in the LBD. The second bar represents the weighted LOCUS sample of private firms,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

Figure 6: Comparison of Firm Employment Distributions (% of emp)




**Notes:** This figure compares the fraction of sample firm-level employment accounted for by each size 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 private firms, where the weights are derived from estimating equations (3) through (5). The third bar represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Figure 7: Comparison 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 private firms, where the weights are derived from estimating equations (3) through (5). The third bar represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

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

| | LOCUS (unweighted) | LOCUS (weighted) | LBD |
|---|---|---|---|
| Single-unit | 20.73% | 46.09% | 53.93% |
| Multi-unit | 79.27% | 53.91% | 46.07% |

**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 private firms, where the weights are derived from estimating equations (3) through (5). The third column represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Table 2: Comparison of Legal Form Distributions (% of emp)

| | LOCUS (unweighted) | LOCUS (weighted) | LBD |
|---|---|---|---|
| Corp. | 42.29% | 46.22% | 47.31 |
| S-Corp., Sole-prop. & Partner. | 12.41% | 43.71% | 36.47 |
| Other | 45.3% | 10.08% | 16.22 |

**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 private firms, where the weights are derived from estimating equations (3) through (5). The third column represents the unweighted LOCUS sample of private firms, where each firm gets equal weight.

Table 3: Summary Statistics table

| | Private | | Public | |
|---|---|---|---|---|
| | mean | stdev | mean | stdev |
| employment | 100 | | 6,200 | |
| age | 11 | | 24 | |
| log(employment) | 1.8 | 1.6 | 6.3 | 2.4 |
| log(age) | 1.9 | 1.2 | 3.0 | 0.7 |
| collateral | 0.17 | 0.24 | 0.24 | 0.23 |
| profitability | 0.13 | 0.40 | 0.22 | 0.34 |
| total leverage | 0.46 | 0.38 | 0.56 | 0.36 |
| financial leverage | 0.16 | 0.24 | 0.21 | 0.24 |
| short-term leverage | 0.04 | 0.11 | 0.03 | 0.08 |
| long-term leverage | 0.12 | 0.22 | 0.18 | 0.21 |
| equity/total assets | 0.48 | 0.38 | 0.44 | 0.36 |

**Notes:** This table compares the mean and standard deviation of key variables for private and public firms. The means and standard deviations are weighted, where the weights are derived from estimating equations (3) through (5). Employment measures firm-level total employment. Age measures the firm age. Collateral is measured as tangible fixed assets over total assets. Profitability is net income over total assets. Total leverage is total liabilities over total assets. Financial leverage is short-term debt plus long-term debt over total assets. Short-term leverage is short-term debt over total assets. Long-term leverage is long-term loans over total assets. Equity/total assets is total shareholder funds over total assets.

# 4 Empirical Methodology and Results

Now that we have accounted for selection and reweighed observations in LOCUS, we can proceed with a standard leverage regression of the form:

$$
\begin{aligned}
LEV_{it} = & \alpha + (\omega_s \times \lambda_t) + \beta_1 \log(EMP_{it}) + \beta_2 AGE_{it} + \beta_3 COLLAT_{it} + \\
& \beta_4 PROFIT_{it} + \beta_5 PROD_{it} + \epsilon_{it}
\end{aligned} \tag{6}
$$

where $i$ is the firm and $t$ is time, measured in years. $(\omega_s \times \lambda_t)$ are sector$\times$year fixed effects, where sector is at the 3-digit level. These fixed effects will account for any time varying sectoral selection effects. Notice that this regression identifies from between firm variation since we do not include firm fixed effects. Inclusion of these fixed effects will render the firm age variable irrelevant since its effect will be absorbed by firm fixed effects and time dummies. Since we are interested in the effect of firm age we will run this regression first and afterwards we drop firm age and introduce firm fixed effects and run a panel version of this regression that identifies from within variation.

The above regression is a standard firm leverage regression with firm collateral ($COLLAT_{it}$) and profitability ($PROFIT_{it}$), where we add $log(EMP_{it})$ and age ($AGE_{it}$) as regressors to capture life-cycle characteristics of firms as determinants of firms leverage. The corporate finance literature also controls for size but mostly using log(assets) as a proxy for size. Given the valuation effects, employment is a more appropriate measure of size since book value of assets will not reflect true size and market value of assets may not reflect true firm growth. The literature also uses cash flow and Tobin's Q as measures of productivity and growth potential. Adding cash flow does not change any of our results. Since 97 percent of our sample is composed of private firms we will not have a Tobin's Q measure. Instead, we use labor productivity ($PROD_{it}$) to control for growth potential.

We focus on three standard measures of leverage as dependent variables: financial debt, short-term debt and long-term debt, each divided by total assets. Both collateral, and profitability are also normalized by assets. In particular, we construct tangible fixed assets to total assets ratio for collateral and net income to total assets ratio for profitability.[27]

[27] profits to total assets is the standard measurue 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

We run regressions separately for listed and private firms. As shown in table 4, among both listed and private firms collateral is positively related to leverage and profitability is negatively related. These results mimic the results in the previous literature. The only exception is the negative sign on collateral for the private firms' short-term borrowing. This is due to a compositional effect. Total leverage for private firms, measured as financial debt to total assets, is positively related to collateral. What may drive the negative coefficient for short-term borrowing is private firms with a lot of collateral switching from short to long term debt.

The new results here are on firm size and age. As previously mentioned, models of financial frictions generally focus only on short-term debt, so let us distinguish between total, short-term and long-term leverage in discussing our results. We find that firm size, measured as log employment, is positively correlated with firm leverage for private firms for all forms of debt. A one standard deviation increase in size is associated with a 24% rise in overall leverage, a 37% rise in short-term leverage, and a 19% rise in long-term leverage. In contrast, public firms' size is negatively correlated with leverage based on short-term debt. In fact, a one standard deviation increase in size is associated with a 13% decline in short-term leverage among public firms.

If we focused on only the listed firms, we would conclude that our results contradict the existing financial frictions literature since this literature (the papers with firm heterogeneity) predicts small firms have lower short-term leverage and larger firms have higher short-term leverage. But private firms, which account for over 60 percent of the economy, tell a different story. The positive correlation between leverage and size supports models featuring decreasing returns to scale and models with explicit heterogeneity in borrowing constraints as a function of size and contradicts models featuring constant returns to scale and a standard borrowing constraint, which predict no relationship between size and leverage. We interpret our finding as showing that size is a measure of financial constraints for private firms but not for listed ones since small private firms cannot borrow short-term while small listed firms can borrow short-term.

Turning to firm age, we find that it plays no significant role for public firms' short-term leverage and a slightly positive role in long-term leverage, which is inconsistent with the theoretical literature predicting a negative relationship. A one standard deviation increase in listed

net income is available, we verify that there is a high correlation between profits over total assets and net income over total assets.

firm age is associated with roughly a 3% rise in long-term leverage. Here again, the experience of private firms is crucial. Private firms borrow more and have higher leverage when they are young. The relationship negative relationship is particularly strong for long-term leverage. A one standard deviation increase in age is associated with about a 12% decline in short-term leverage and a 20% decline in long-term leverage. This is consistent with financial frictions models, which predict, conditional on size, that firms pay down long-term debt as they age. Once more, these results show that age is not a good proxy for financial constraints, but rather size appears to be a more appropriate proxy of such constraints.

Table 4: Leverage Regressions for Private & Listed Firms (2005-2012)

| | ($FD/TA_{it}$) | | ($STL/TA_{it}$) | | ($LTL/TA_{it}$) | |
|---|---|---|---|---|---|---|
| | Listed | Private | Listed | Private | Listed | Private |
| $\log(EMP_{it})$ | 0.0178*** | 0.0281*** | -0.0014*** | 0.0117*** | 0.0195*** | 0.0167*** |
| | (0.0008) | (0.0007) | (0.0003) | (0.0003) | (0.0007) | (0.0006) |
| $AGE_{it}$ | 0.0007*** | -0.0024*** | 0.0001 | -0.0004*** | 0.0006*** | -0.0019*** |
| | (0.0002) | (0.0001) | (0.0001) | (0.0000) | (0.0002) | (0.0001) |
| $COLLAT_{it}$ | 0.2321*** | 0.1861*** | 0.0265*** | -0.0296*** | 0.2023*** | 0.2118*** |
| | (0.0112) | (0.0049) | (0.0043) | (0.0021) | (0.0102) | (0.0045) |
| $PROFIT_{it}$ | -0.1928*** | -0.0702*** | -0.0688*** | -0.0290*** | -0.1178*** | -0.0402*** |
| | (0.0090) | (0.0037) | (0.0044) | (0.0019) | (0.0076) | (0.0030) |
| $PROD_{it}$ | 0.0061*** | 0.0087*** | 0.0009 | 0.0088*** | 0.0053*** | -0.0000 |
| | (0.0020) | (0.0011) | (0.0007) | (0.0006) | (0.0018) | (0.0009) |
| Constant | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Wgts (logit) | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 20,000 | 320,000 | 20,000 | 320,000 | 20,000 | 320,000 |
| R2 | 0.2299 | 0.1525 | 0.1164 | 0.0882 | 0.2275 | 0.1523 |

**Notes:** We consider unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variables are financial debt/total assets ($FD/TA_{it}$) in the first two columns, short-term debt/total assets ($STL/TA_{it}$) in the next two columns, and long-term loans/total assets ($LTL/TA_{it}$) in the last two columns. The main regressors are $\log(EMP_{it})$ to measure firm size; $AGE_{it}$ to measure firm age; $COLLAT_{it}$ to measure tangible fixed assets over total assets; $PROFIT_{it}$ to measure net income over total assets; and $PROD_{it}$ to measure log labor productivity. All regressions include a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively.

We now verify whether our firm size results hold beyond the cross-sectional setting. To do so, we drop age as a regressor, lag all regressors by one period, and introduce firm fixed-effects. That is we run:

$$\begin{aligned} LEV_{it} = &\alpha_i + (\omega_s \times \lambda_t) + \beta_1 \log(EMP_{it-1}) + +\beta_2 COLLAT_{it-1} + \\ &\beta_3 PROFIT_{it-1} + \beta_4 PROD_{it-1} + \epsilon_{it} \end{aligned} \tag{7}$$

We focus on a balanced sub-sample of firms for which we have data over the period 2005 through 2011, and run regressions separately for private and listed firms.[28] From the theoretical financial frictions literature, we would anticipate that leverage rises as firms grow due to loosening financial constraints. Since these models primarily focus on short-term lending, we are particularly interested in the relationship between short-term leverage and size. As table 5 shows, we do find that leverage and employment are positively related in a longitudinal panel setting. This finding is noteworthy since in the leverage regression upon inclusion of fixed effects, no determinant remains significant in general. As expected, in our case, results are driven by private firms, which are subject to more financial frictions than listed firms, and short-term leverage, which is precisely the focus of financial frictions models.

## 4.1 Nonlinear Relationships

To explore possible non-linearities in the relationship between leverage, size and age we run a series of quadratic regressions. We run the regression specified in the previous section separately for public and private firms, and introduce a quadratic term for employment (figures 8 through 10) or age (figures 11 through 13).[29] Since financial debt is primarily composed of long-term loans financial leverage behaves as long-term leverage does. As a result, we only report figures associated with financial debt over total assets and short-term loans over total assets. We also consider total equity over total assets to get a sense of how firms might be substituting between debt and equity financing.

[28] Orbis coverage of firms in 2012 is limited because it is the end of the data collection period and there are reporting and data gathering lags. We therefore restrict ourselves to the period 2005–2011 in constructing our balanced sample.

[29] Each figure plots the predicted values of the dependent variable as a function of the independent variable of interest (size or age), holding all other variables at their sample means.

Table 5: Balanced Panel (2005-2011)

| | (Listed) | | | (Private) | | |
|---|---|---|---|---|---|---|
| | FD/TA$_{it}$ | STL/TA$_{it}$ | LTL/TA$_{it}$ | FD/TA$_{it}$ | STL/TA$_{it}$ | LTL/TA$_{it}$ |
| log(EMP$_{it-1}$) | 0.0072 | 0.0024 | 0.0025 | 0.0101 | 0.0066$^{**}$ | 0.0027 |
| | (0.0057) | (0.0024) | (0.0051) | (0.0069) | (0.0033) | (0.0061) |
| COLLAT$_{it-1}$ | 0.1199$^{***}$ | 0.0097 | 0.1134$^{***}$ | 0.0463$^{***}$ | -0.0019 | 0.0495$^{***}$ |
| | (0.0344) | (0.0156) | (0.0333) | (0.0141) | (0.0101) | (0.0148) |
| PROFIT$_{it-1}$ | -0.0516$^{***}$ | -0.0230$^{***}$ | -0.0333$^{***}$ | 0.0091 | -0.0001 | 0.0123 |
| | (0.0098) | (0.0056) | (0.0105) | (0.0102) | (0.0034) | (0.0097) |
| PROD$_{it-1}$ | -0.0037 | -0.0005 | -0.0033 | -0.0027 | 0.0017 | -0.0039 |
| | (0.0049) | (0.0014) | (0.0047) | (0.0054) | (0.0026) | (0.0048) |
| Industry-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Wgts (logit) | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 10,000 | 10,000 | 10,000 | 19,000 | 19,000 | 17,000 |
| R2 | 0.8637 | 0.5542 | 0.8410 | 0.7720 | 0.6271 | 0.7904 |

**Notes:** We consider balanced samples of private and publicly-listed firms separately between the years 2005 and 2011. The dependent variables are financial debt/total assets (FD/TA$_{it}$), short-term debt/total assets (STL/TA$_{it}$), and long-term loans/total assets (LTL/TA$_{it}$) in the last two columns. The main regressors are log(EMP$_{it-1}$) to measure firm size; COLLAT$_{it-1}$ to measure tangible fixed assets over total assets; PROFIT$_{it-1}$ to measure net income over total assets; and PROD$_{it-1}$ to measure log labor productivity. All regressions include a full set of 3-digit industry-year fixed effects and firm fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively.

We run the following regressions to estimate the non-linear relation between size and leverage and age and leverage:

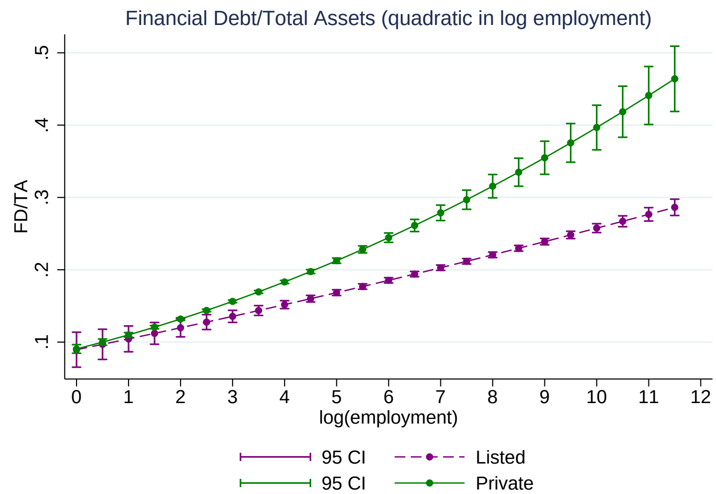
$$\begin{aligned} LEV_{it} =& \alpha + (\omega_s \times \lambda_t) + \beta_1 \log(SIZE_{it}) + \beta_2 \log(SIZE_{it})^2 + \beta_3 AGE_{it} + \beta_4 COLLAT_{it} + \\ & \beta_5 PROFIT_{it} + \beta_6 PROD_{it} + \epsilon_{it} \end{aligned} \tag{8}$$

$$\begin{aligned} LEV_{it} =& \alpha + (\omega_s \times \lambda_t) + \beta_1 AGE_{it} + \beta_2 AGE_{it}^2 + \beta_3 \log(SIZE_{it}) + \beta_4 COLLAT_{it} + \\ & \beta_5 PROFIT_{it} + \beta_6 PROD_{it} + \epsilon_{it} \end{aligned} \tag{9}$$

Focusing first on the figures with quadratic employment, we see that size is more strongly positively associated with debt financing (both overall and short-term) among private firms than public ones (figure 8 and 9). In fact, there is no relation between size and short-term leverage for listed firms. This finding is consistent with private firms facing more financial frictions than listed ones. Note also that there is a logarithmically convex relationship between long-term leverage and size for private firms, but the short-term leverage and size relationship appears more logarithmically concave. Moreover, among private firms there is a strong negative relationship between total equity over total assets and employment (figure 10). One interpretation is that as financial constraints ease, private firms choose debt financing over internal equity.

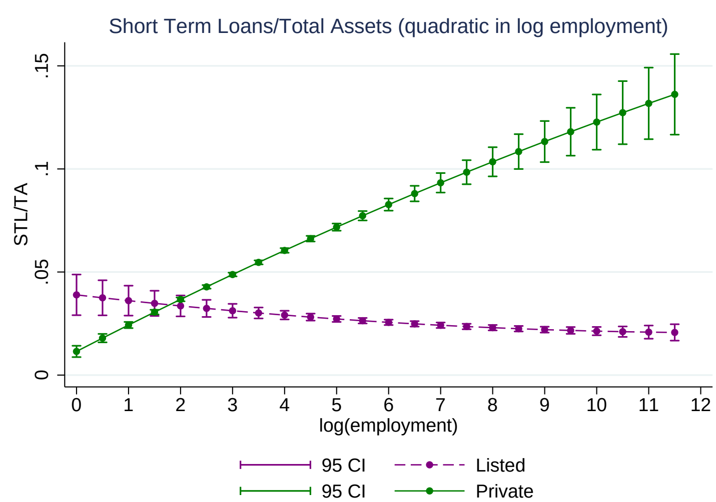
The equity-size relationship has more of an inverted U-shape for public firms. Since these firms have access to external equity via stock issuances, one interpretation is that small and medium sized listed firms complement long-term debt with external equity. As they become larger, they issue less external equity and turn toward long-term debt borrowing.

Figure 8: Quadratic Relationship between FD/TA and Size



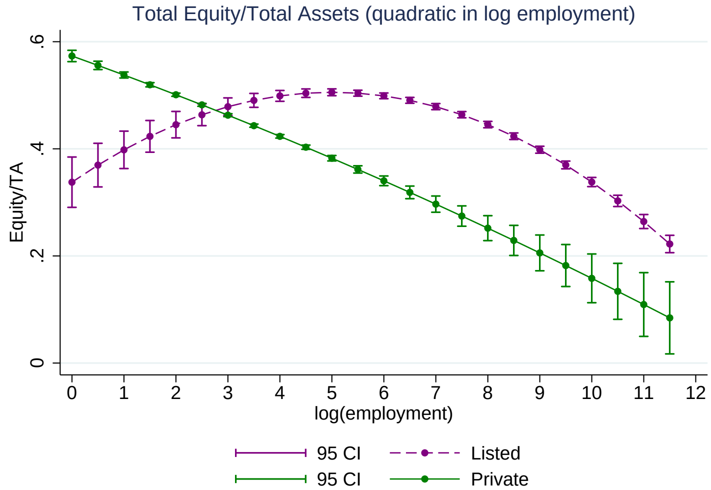

**Notes:** Use unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variable is financial debt/total assets (FD/$TA_{it}$). Each line shows the conditional relationship between firm size (log($EMP_{it}$)) and leverage, where we allow for some flexibility by introducing a quadratic term for employment. The figures condition on $AGE_{it}$ to measure firm age; $COLLAT_{it}$ to measure tangible fixed assets over total assets; $PROFIT_{it}$ to measure net income over total assets; and $PROD_{it}$ to measure log labor productivity; and a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

Figure 9: Quadratic Relationship between STL/TA and Size




**Notes:** Use unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variable is short-term loans/total assets (STL/$TA_{it}$). Each line shows the conditional relationship between firm size (log($EMP_{it}$)) and leverage, where we allow for some flexibility by introducing a quadratic term for employment. The figures condition on $AGE_{it}$ to measure firm age; $COLLAT_{it}$ to measure tangible fixed assets over total assets; $PROFIT_{it}$ to measure net income over total assets; and $PROD_{it}$ to measure log labor productivity; and a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

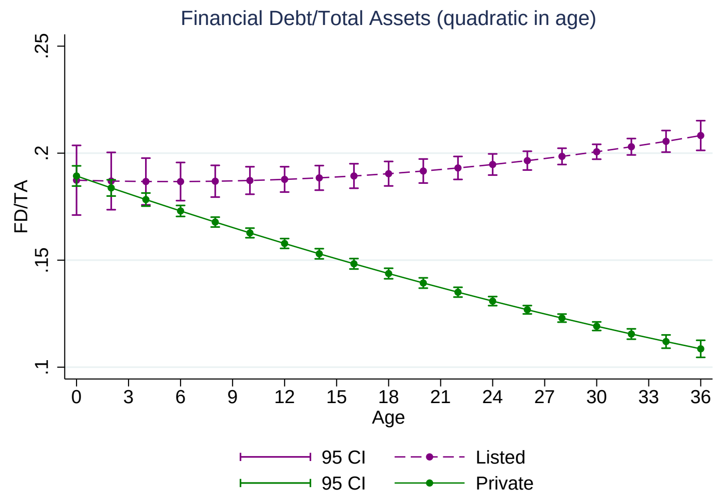
Figure 10: Quadratic Relationship between Equity/TA and Size




**Notes:** Use unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variable is total equity/total assets (Equity/TA$_{it}$), where total equity includes both internal and external equity. Each line shows the conditional relationship between firm size (log(EMP$_{it}$)) and leverage, where we allow for some flexibility by introducing a quadratic term for employment. The figures condition on AGE$_{it}$ to measure firm age; COLLAT$_{it}$ to measure tangible fixed assets over total assets; PROFIT$_{it}$ to measure net income over total assets; and PROD$_{it}$ to measure log labor productivity; and a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

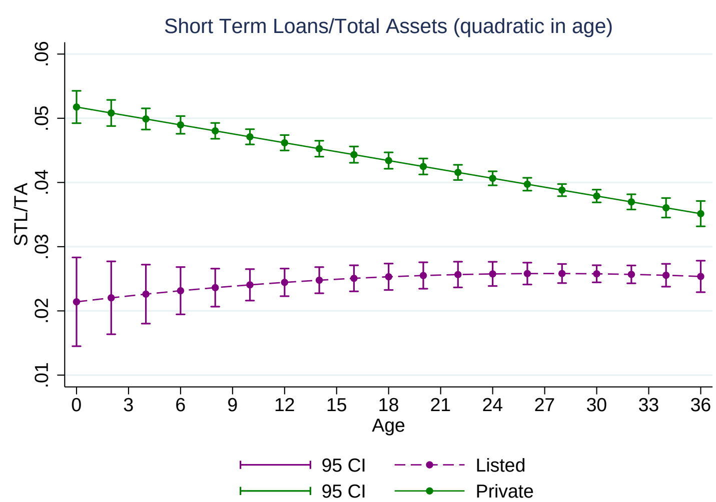
Turning now to figures that are quadratic in age. Private firms appear to draw down short-term leverage as they age, which is consistent with theories in which entrepreneurs borrow to start their businesses and then pay off their loans as they age (figures 11 and 12). This is consistent with what we see in figure 13 where private firms raise internal equity as they age, while paying down their short-term loans. The relationship between age and leverage is far weaker and quite flat among public firms in all measures of leverage. Public firms appear to slightly reduce their equity as they age. This behavior is consistent with large public firms being leveraged in long term debt – as they grow older, they also become larger. Though confidence intervals are not very tight for these relations for listed firms.

Figure 11: Quadratic Relationship between FD/TA and Age



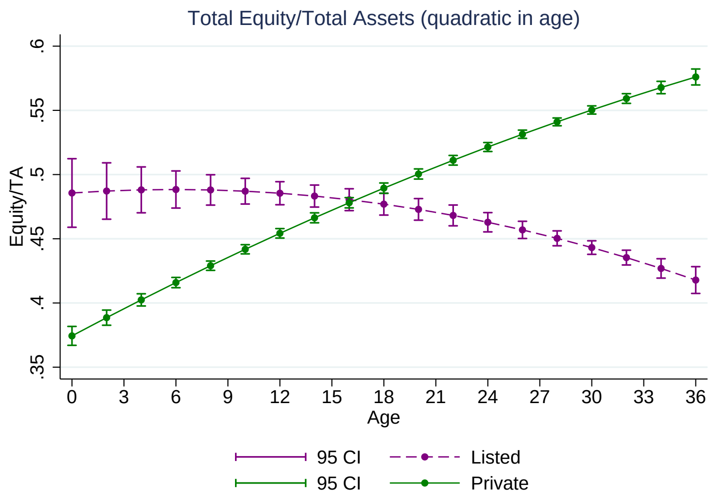

**Notes:** Use unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variable is financial debt/total assets (FD/TA$_{it}$). Each line shows the conditional relationship between firm age and leverage, where we allow for some flexibility by introducing a quadratic term for age (AGE$_{it}$). The figures condition on log(EMP$_{it}$) to measure firm size; COLLAT$_{it}$ to measure tangible fixed assets over total assets; PROFIT$_{it}$ to measure net income over total assets; and PROD$_{it}$ to measure log labor productivity; and a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

Figure 12: Quadratic Relationship between STL/TA and Age




**Notes:** Use unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variable is short-term loans/total assets (STL/TA$_{it}$). Each line shows the conditional relationship between firm age and leverage, where we allow for some flexibility by introducing a quadratic term for age (AGE$_{it}$). The figures condition on log(EMP$_{it}$) to measure firm size; COLLAT$_{it}$ to measure tangible fixed assets over total assets; PROFIT$_{it}$ to measure net income over total assets; and PROD$_{it}$ to measure log labor productivity; and a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

Figure 13: Quadratic Relationship between Equity/TA and Age




**Notes:** Use unbalanced samples of private and publicly-listed firms separately between the years 2005 and 2012. The dependent variable is total equity/total assets (Equity/$\text{TA}_{it}$), where total equity includes both internal and external equity. Each line shows the conditional relationship between firm age and leverage, where we allow for some flexibility by introducing a quadratic term for age ($\text{AGE}_{it}$). The figures condition on log($\text{EMP}_{it}$) to measure firm size; $\text{COLLAT}_{it}$ to measure tangible fixed assets over total assets; $\text{PROFIT}_{it}$ to measure net income over total assets; and $\text{PROD}_{it}$ to measure log labor productivity; and a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

## 4.2 Response to Shocks: Evidence from Great Recession

Since LOCUS spans the Great Recession, we can investigate whether the life-cycle patterns we observe change during the financial shock of 2009–2012. Again, we decompose financial leverage into short-term and long-term leverage in table 6. Focusing on the pre-crisis period (2005–2008), we see similar results as before, where the experience of private firms is consistent with financial frictions models with decreasing returns to scale. Larger firms are less financially constrained and therefore have higher leverage. The relationship is stronger for short-term leverage than long-term leverage. A one standard deviation increase in size during this period is associated with a 43% increase in short-term leverage and a 16% increase in long-term leverage. Older firms pay down their long-term debt, resulting in a negative relationship between long-term leverage and age. The relationship is stronger, as predicted in theory, for long-term leverage. A one standard deviation increase in age is associated with a 9% decline in short-term leverage and a 20% decline in long-term leverage. Listed firms are less leveraged in terms of both short-term and long-term debt than private firms. Moreover, since these listed firms are likely less affected by financial frictions their experience is inconsistent with theory. In particular, we do not find a positive relationship between public firms' size and short-term leverage and age is positively correlated with leverage.

However, during the crisis (2009–2012), when both public and private firms are likely to be affected by financial frictions the differences between them are dampened. Listed firms remain less leveraged than private firms. Older public firms pay down their long-term leverage, similar to private firms. A one standard deviation increase in age is associated with 15% decline in short-term leverage among private firms and a 2% decline among listed firms. Even during the crisis listed firms remain relatively less financially constrained than private firms since there is even a negative relationship between size and short-term leverage. A one standard deviation increase in size among private firms is associated with a 32% increase in short-term leverage and a 9% decline among public firms.

### 4.3 Nonlinear Relationships During the Great Recession

In the previous sections we argued that size (employment) is an informative correlate of financial constraints. We found that listed firms are less affected by financial constraints than private firms both before and after the financial crisis. In this section, we dig further into the relationship between leverage and size during the Great Recession.

In figures 14 and 15 we plot the quadratic relationship between size and short-term leverage for private (figure 14) and listed (figure 15) firms before the crisis in 2006 and during the crisis in 2009. To generate this figure and the next, we run a regression of short-term leverage on size, size squared and industry fixed effects for private firms (figure 14) and listed firms (figure 15) separately for 2006 and 2009.

$$STLEV_i = \alpha + \omega_s + \beta_1 \log(SIZE_i) + \beta_2 \log(SIZE_i)^2 + \epsilon_i \tag{10}$$

where $STLEV_i$ is short-term debt over total assets, $\omega_s$ captures industry fixed effects, and $SIZE_i$ is measured by either employment or total assets. This specification is a close empirical counterpart to the size-dependent collateral constraints arising in macroeconomic models with financial frictions where constraints are a function of firm size or models with decreasing returns to scale. [30]

In the left panel of figure 14, we measure size by employment and in the right panel by

[30] In section C of the appendix, figures 18 and 19 show the results when, in addition to industry fixed effects, we control for labor productivity, collateral, profitability and age. The figures are qualitatively consistent with the figures presented in the main text without the additional controls.

Table 6: Pooled Regressions: Short-term debt/total assets & Long-term debt/total assets

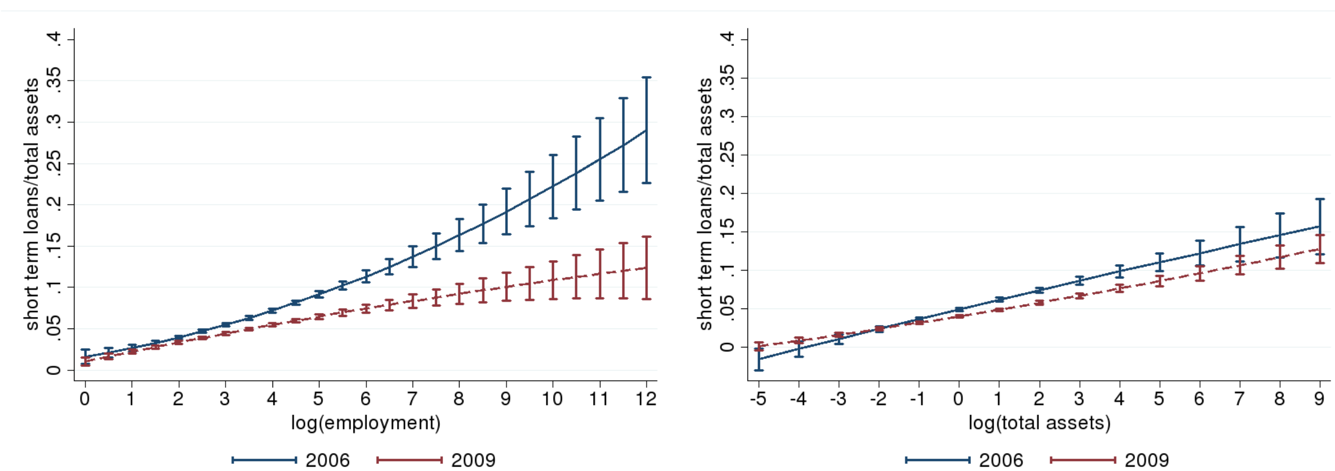
| | (2005-2012) | | (2005-2008) | | (2009-2012) | |
|---|---|---|---|---|---|---|
| | $STL/TA_{it}$ | $LTL/TA_{it}$ | $STL/TA_{it}$ | $LTL/TA_{it}$ | $STL/TA_{it}$ | $LTL/TA_{it}$ |
| $\log(EMP_{it})$ | 0.0117*** | 0.0167*** | 0.0158*** | 0.0176*** | 0.0085*** | 0.0160*** |
| | (0.0003) | (0.0006) | (0.0004) | (0.0009) | (0.0005) | (0.0009) |
| AGE | -0.0004*** | -0.0019*** | -0.0004*** | -0.0026*** | -0.0004*** | -0.0013*** |
| | (0.0000) | (0.0001) | (0.0000) | (0.0001) | (0.0001) | (0.0001) |
| $COLLAT_{it}$ | -0.0296*** | 0.2118*** | -0.0335*** | 0.2425*** | -0.0200*** | 0.1732*** |
| | (0.0021) | (0.0045) | (0.0025) | (0.0062) | (0.0036) | (0.0064) |
| $PROFIT_{it}$ | -0.0290*** | -0.0402*** | -0.0297*** | -0.0402*** | -0.0281*** | -0.0405*** |
| | (0.0019) | (0.0030) | (0.0020) | (0.0039) | (0.0037) | (0.0045) |
| $PROD_{it}$ | 0.0088*** | -0.0000 | 0.0128*** | -0.0001 | 0.0055*** | 0.0003 |
| | (0.0006) | (0.0009) | (0.0007) | (0.0013) | (0.0009) | (0.0013) |
| $PUBLIC_i$ | -0.0236*** | -0.0964*** | -0.0211*** | -0.1040*** | -0.0208*** | -0.0702*** |
| | (0.0030) | (0.0065) | (0.0042) | (0.0088) | (0.0043) | (0.0095) |
| $\log(EMP_{it})$ x $PUBLIC_i$ | -0.0129*** | 0.0004 | -0.0169*** | -0.0027** | -0.0095*** | 0.0050*** |
| | (0.0005) | (0.0010) | (0.0006) | (0.0014) | (0.0007) | (0.0014) |
| $AGE_{it}$ x $PUBLIC_i$ | 0.0006*** | 0.0025*** | 0.0005*** | 0.0034*** | 0.0004*** | 0.0007*** |
| | (0.0001) | (0.0002) | (0.0001) | (0.0003) | (0.0001) | (0.0003) |
| $COLLAT_{it}$ x $PUBLIC_i$ | 0.0507*** | -0.0081 | 0.0535*** | -0.0594*** | 0.0445*** | 0.0481*** |
| | (0.0042) | (0.0093) | (0.0058) | (0.0128) | (0.0061) | (0.0134) |
| $PROFIT_{it}$ x $PUBLIC_i$ | -0.0376*** | -0.0782*** | -0.0346*** | -0.0800*** | -0.0408*** | -0.0694*** |
| | (0.0048) | (0.0082) | (0.0062) | (0.0111) | (0.0076) | (0.0119) |
| $PROD_{it}$ x $PUBLIC_i$ | -0.0114*** | 0.0041** | -0.0133*** | 0.0033 | -0.0106*** | 0.0038 |
| | (0.0008) | (0.0019) | (0.0011) | (0.0025) | (0.0012) | (0.0028) |
| Constant | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Wgts (logit) | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 340,000 | 340,000 | 160,000 | 160,000 | 180,000 | 180,000 |
| R2 | 0.0882 | 0.1523 | 0.0864 | 0.1478 | 0.0931 | 0.1307 |

**Notes:** We consider a pooled unbalanced samples of private and publicly-listed firms between the periods 2005-2012 in the first two columns, 2005-2008 in the next two columns and 2009-2012 in the last two columns. The dependent variables are short-term loans/total assets ($STL/TA_{it}$) and long-term debt/total assets ($LTL/TA_{it}$). The main regressors are $\log(EMP_{it})$ to measure firm size; $AGE_{it}$ to measure firm age; $COLLAT_{it}$ to measure tangible fixed assets over total assets; $PROFIT_{it}$ to measure net income over total assets; and $PROD_{it}$ to measure log labor productivity; a publicly-listed dummy indicating whether a firm is actively publicly traded; and a full set of interaction terms. The coefficients on the uninteracted regressors denotes the marginal effect of each regressor on leverage among the privately-held firms. The interacted terms indicated the extra boost (or dampening) effect of being publicly traded. All regressions include a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively.

total assets. Consistent with our prior results, for private firms there is a positive correlation between size (employment and total assets) and short-term leverage in both years. The relationship becomes flatter during the crisis (2009). When size is measured by employment, the relationship between size and leverage is significantly weaker in 2009 than it was in 2006. The pattern is consistent with private firms becoming more financially constrained in 2009 or demanding less bank financing during this period.

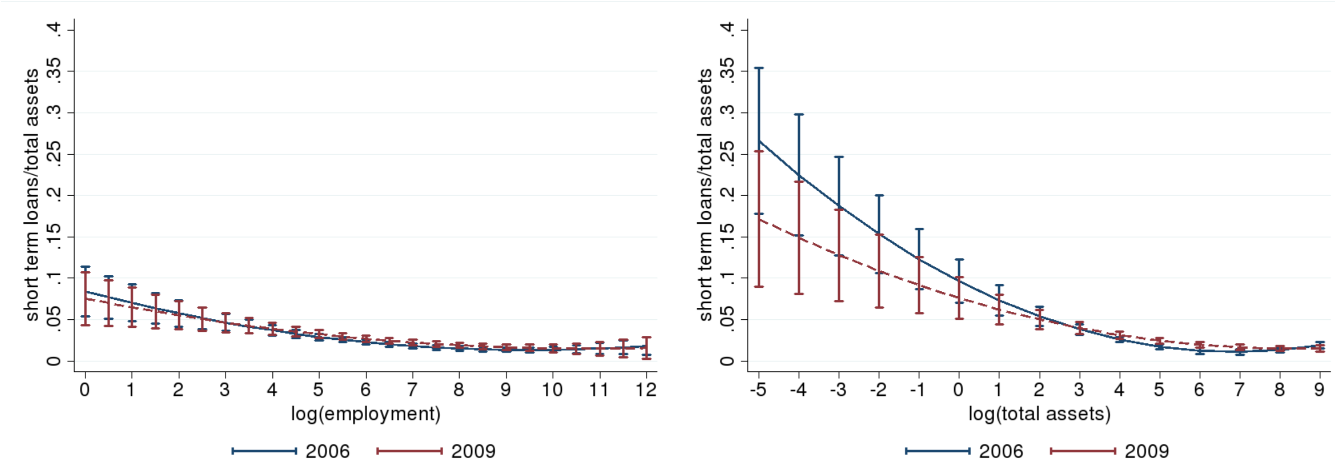
In contrast, figure 15 shows that for listed firms the relationship between leverage and size is negative in both 2006 and 2009 and when size is measured by employment and total assets. Moreover, we do not observe a significant difference in the size-leverage relationship in 2006 and 2009. These results are consistent with our previously reported regression results and suggest that listed firms are less affected by financial frictions both before and during the Great Recession. The results also highlight the importance of data on private firms since not only is the relationship between leverage and size weaker for public firms, it also has the opposite sign.

Figure 14: Relationship between short-term leverage and size for private firms (2006 & 2009)




**Notes:** Use unbalanced sample of private firms separately for 2006 and 2009. The dependent variable is short-term leverage (STLEV). Each line shows the relationship between leverage, size (measured by employment in the left panel and total assets in the right figure) and size squared, controlling only for a full set of 3-digit industry fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

Figure 15: Relationship between short-term leverage and size for public firms (2006 & 2009)




**Notes:** Use unbalanced sample of public firms separately for 2006 and 2009. The dependent variable is short-term leverage (STLEV). Each line shows the between leverage, size (measured by employment in the left panel and total assets in the right figure) and size squared, controlling only for a full set of 3-digit industry fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

## 4.4 Firm Growth During Normal Times and the Great Recession

These results have important implications for the aggregate economy as long as financial frictions affect real outcomes. In this section, we complement our analysis of the relationship between leverage and firm life-cycle characteristics with an analysis of the relationship between leverage and revenue growth. We first consider the following cross-sectional regression (first three columns of table 7).

$$\begin{aligned} RG_{it} =& \alpha + (\omega_s \times \lambda_t) + \beta_1 STLEV_{it-1} + \beta_2 (STLEV_{it-1} \times PUBLIC_i) + \beta_3 (STLEV_{it-1} \times CRISIS_t) + \\ & \beta_4 (STLEV_{it-1} \times PUBLIC_i \times CRISIS_t) + \mathbf{\Gamma}' Z_{it-1} + \epsilon_{it} \end{aligned} \tag{11}$$

where $RG$ is revenue growth, measured as $\frac{REV_{it} - REV_{it-1}}{0.5(REV_{it} + REV_{it-1})}$; $(\omega_s \times \lambda_t)$ captures industry-year fixed effects and $STLEV_{it}$ is short-term debt over total assets. $STLEV_{it}$ is interacted with a dummy equal to one if the firm is publicly-listed ($PUBLIC_i$), a dummy equal to one during the financial crisis (2008 and 2009), and both $PUBLIC_i$ and $CRISIS_t$. $Z_{it-1}$ includes firm age ($AGE_{it-1}$), log revenue ($\log(REV_{it-1})$), profitability ($PROFIT_{it-1}$), and labor productivity ($PROD_{it-1}$). Each of these additional controls is included on its own, interacted with $PUBLIC_i$, interacted with $CRISIS_t$ and interacted with both $PUBLIC_i$ and $CRISIS_t$. In addition to the cross-sectional specification, we also report results using firm fixed effects (last three columns of table 7):

$$
\begin{aligned}
RG_{it} = & \alpha_i + (\omega_s \times \lambda_t) + \beta_1 STLEV_{it-1} + \beta_2 (STLEV_{it-1} \times PUBLIC_i) + \beta_3 (STLEV_{it-1} \times CRISIS_t) + \\
& \beta_4 (STLEV_{it-1} \times PUBLIC_i \times CRISIS_t) + \mathbf{\Gamma}' Z_{it-1} + \epsilon_{it}
\end{aligned}
\tag{12}
$$

Table 7 reports the results of the cross-sectional specification in the first three columns and the firm fixed effects specification in the last three columns. The first and fourth columns do not include any interaction terms and show that there exists a positive relationship between short-term borrowing and revenue growth, though the significance is weaker in column (4) with firm fixed effects. The fifth and sixth columns explain why this is the case. The second and fifth columns introduce interactions with $PUBLIC_i$ and highlight that the positive relationship between firm growth and leverage is driven entirely by private firms. In fact, the relationship between short-term leverage and growth is negative for listed firms. This negative relationship may be indicative of listed firms relying more heavily on different forms of financing, such as long-term debt, than private firms. In columns three and six, we focus on the crisis period ($CRISIS_t$). The negative relationship between leverage and growth for public firms is independent of crisis. The relationship between short-term leverage and growth also does not change in the cross section of *private* firms but becomes weaker during crisis in the firm fixed effect specification for the private firms. When we calculate the total effect of leverage on growth for private firms during crisis, we find that this effect is basically insignificant. We observe no difference between private and public firms during crisis periods in terms of their growth-leverage relationship as shown with triple interaction in columns three and six.

Our analysis of the relationship between revenue growth and leverage further highlights the importance of using data on private firms since the relationship between growth and short-term leverage differs substantially between private and listed firms. Overall our empirical analysis using LOCUS dataset indicates that to obtain a more complete picture of the implications of financial frictions for the broader economy, it is important to take into account, in addition to public firms, private firms that account for over half of the employment and revenue in the U.S. economy. The findings also caution testing of theories incorporating financial frictions at the firm level using data on publicly traded firms only. The stark differences in the life-cycle leverage patterns exhibited by public versus private firms point to a need for a more nuanced approach to modeling financial frictions for these two types of firms. In addition, the differences between the two groups of firms matter for macro models that study the interaction between financial frictions and aggregate shocks. Both groups are clearly large enough to be influential in macro outcomes, and the differential response of the two groups to shocks should be taken into account when studying the consequences of aggregate shocks.

Table 7: Growth Regressions

| | (1)<br>$RG_{it}$ | (2)<br>$RG_{it}$ | (3)<br>$RG_{it}$ | (4)<br>$RG_{it}$ | (5)<br>$RG_{it}$ | (6)<br>$RG_{it}$ |
|---|---|---|---|---|---|---|
| $STLEV_{t-1}$ | 0.1013*** | 0.1023*** | 0.0829*** | 0.0524* | 0.0530* | 0.0802*** |
| | (0.0216) | (0.0216) | (0.0255) | (0.0276) | (0.0277) | (0.0292) |
| $STLEV_{t-1} \times PUBLIC_i$ | | -0.3588*** | -0.3650*** | | -0.2726*** | -0.3546*** |
| | | (0.0814) | (0.0968) | | (0.0824) | (0.0964) |
| $STLEV_{t-1} \times CRISIS_t$ | | | 0.0536 | | | -0.0793** |
| | | | (0.0440) | | | (0.0351) |
| $STLEV_{t-1} \times PUBLIC_i \times CRISIS_t$ | | | 0.0291 | | | 0.2215 |
| | | | (0.1721) | | | (0.1575) |
| $\log(REV)_{t-1}$ | -0.0122*** | -0.0124*** | -0.0056* | -0.4923*** | -0.4933*** | -0.4959*** |
| | (0.0027) | (0.0027) | (0.0031) | (0.0164) | (0.0165) | (0.0159) |
| $\log(REV)_{t-1} \times PUBLIC_i$ | | 0.0123*** | 0.0046 | | 0.1839*** | 0.1895*** |
| | | (0.0033) | (0.0038) | | (0.0297) | (0.0296) |
| $\log(REV)_{t-1} \times CRISIS_t$ | | | -0.0198*** | | | 0.0059 |
| | | | (0.0057) | | | (0.0039) |
| $\log(REV)_{t-1} \times PUBLIC_i \times CRISIS_t$ | | | 0.0227*** | | | -0.0027 |
| | | | (0.0074) | | | (0.0040) |
| Industry-Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | No | No | No | Yes | Yes | Yes |
| Weights | Yes | Yes | Yes | Yes | Yes | Yes |
| Full set of controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Obs. | 144,000 | 144,000 | 144,000 | 144,000 | 144,000 | 144,000 |
| R-sq | 0.0759 | 0.0760 | 0.0804 | 0.6140 | 0.6142 | 0.6144 |
| private | | 0.0000 | 0.0012 | | 0.0563 | 0.0062 |
| public | | 0.0009 | 0.0028 | | 0.0029 | 0.0025 |
| private-crisis | | | 0.0002 | | | 0.9822 |
| public-crisis | | | 0.0834 | | | 0.6823 |

**Notes:** We consider a pooled unbalanced sample of publicly listed firms between the periods 2005-2012. The dependent variable is the firm-level revenue growth rate. The first three columns are cross-sectional and the last three control for firm-fixed effects. The main regressors are short-term leverage ($STLEV_{it}$), revenue ($\log(REV_{it-1})$), firm age ($AGE_{it-1}$), profitability ($PROFIT_{it-1}$), and labor productivity ($PROD_{it-1}$). All regressors are lagged and interacted with a public dummy ($PUBLIC_i$), crisis dummy ($CRISIS_t$), and the both ($PUBLIC_i \times CRISIS_t$). All regressions include a full set of 3-digit industry-year fixed effects. All observations are weighted to adjust for selection into the LOCUS sample, as detailed in section 3. Standard errors are robust. ***, **, and * indicates significance at the 1%, 5%, and 10% levels,respectively. The last four lines of the table report the p-value of the total effects for: 1) "private" ($STLEV_{it-1}$) – private firms in normal times; 2) "public" ($STLEV_{it-1} + STLEV_{it-1} \times PUBLIC_i$) – listed firms in normal times; 3) "private-crisis" ($STELV_{it-1} + STLEV_{it-1} \times CRISIS_t$) – private firms in the financial crisis; and 4) "public-crisis" ($STLEV_{it-1} + STLEV_{it-1} \times PUBLIC_i + STLEV_{it-1} \times PUBLIC_i \times CRISIS_t$) – listed firms in the financial crisis.

# 5 Conclusion

We construct a new data set, LOCUS, that provides information on financials of private firms in the U.S. to study the firm life-cycle dynamics of firm financing, and its implications on firm growth and responsiveness to aggregate shocks. To provide a broad picture for both public and private firms, we match financial data for privately-held firms in Orbis and publicly-listed firms in Compustat to U.S. Census Bureau's Longitudinal Business Database. This match allows us to account for selection in Orbis, and to also include administrative data on employment - a key variable that is not available in Orbis.

Our results indicate that, conditional on firm age and other observables that can affect firm borrowing, small private firms may be more financially constrained given the strong positive correlation between firm size and short term leverage, both in cross-section and over time, whereas leverage of public firms is largely independent of their size. The relationship between size and short-term leverage is non-linear and slightly concave for private firms, whereas for public firms it is flat. Firm age, after controlling for firm size and other observables, turns out not to be a proxy for financial constraints, since young firms tend to borrow more and pay down their debt as they grow older. We find that very large public firms stay highly leveraged in terms of long term debt, even when they get older, while private firms switch from debt to equity financing, as they age.

Using Great Recession as an aggregate shock, we show that, the positive and non-linear relationship between size and short-term leverage becomes more linear during the recession, as large private firms reduce their leverage more. For public firms, the relation between short-term leverage and size does not change during the crisis and stays flat. This finding supports our interpretation that public firms are never constrained, while small private firms are constrained during normal times, and large private firms might also get constrained during crisis times. These findings might also have a different interpretation based on demand shocks that can reduce borrowing by firms. It might be the case that demand shocks that are relevant for the period 2007 and after might have a disproportionate effect on larger private firms. We control for firm-level profitability and sector-year fixed effects to account for such shocks though we still cannot rule out fully the effects of firm-level unobserved demand shocks.

The implications of life-cycle leverage on firm growth are as follows. Private firms finance their growth mainly through short-term debt during normal times. During the Great Recession, the strong positive relation between short-term leverage and private firm growth stays in the cross-section but gets weaker during crisis when we use firm fixed effects. If these fixed effects capture unobserved and time invariant firm-level low demand during crisis years, then private firms which entered the crisis with higher short-term leverage grow less during crisis, which might be due to a deleveraging effect. It may also be the case that these firms were affected more from time varying negative demand shocks. Again, for public firms there is no effect of crisis in terms of the relation between leverage and firm growth.

Our results for private firms are consistent with some theories of firm dynamics and financing, whereas the behavior of listed firms is substantially different and cannot be explained by the existing models. Since most of the existing models rely on full firm size distribution, it is not surprising that the results for listed firms do not square with these models. An important implication of our results is that macro-finance models should not be relying *solely* on data moments extracted from listed firm samples for their calibration exercises.

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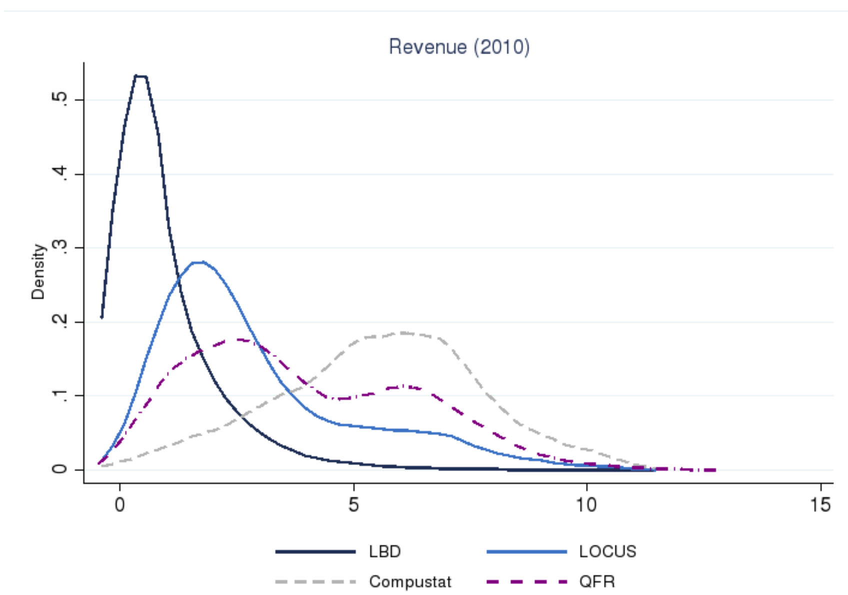
# A Comparison of LOCUS and QFR data

Although QFR surveys both small and large firms in the manufacturing sector, LOCUS has better coverage of small firms. To be consistent with figures 3 and 4, we focus on the year 2010. Since coverage in the QFR is greatest in the manufacturing sector, we also focus on this sector in the LBD, Compustat, and LOCUS. In the figure 16, we plot the distribution of real revenue, which is available for all four data sources. The three non-LBD data sources have a greater mass of large firms than the LBD. While QFR contains smaller firms than Compustat, the LOCUS distribution of real revenue is closer that of the LBD than QFR.

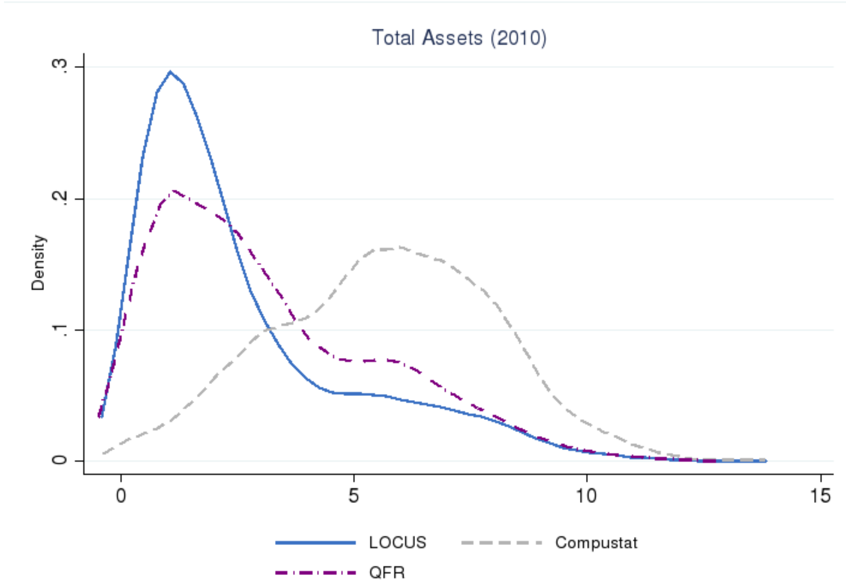
In figure 17, we plot the distribution of log real total assets for the three data sources where this variable is available – Compustat, LOCUS and QFR. Again, we see that while QFR's coverage of small firms is better than Compustat, it is worse than LOCUS. Moreover, LOCUS contains data on both small and large firms in sectors outside of manufacturing, while QFR surveys only large firms outside of manufacturing.

Figure 16: Comparison of Revenue Distributions (2010, Manufacturing Sector)




**Notes:** This figure compares the distribution of firm-level revenue in the manufacturing sector across four samples in 2010. The first sample contains firms in the LBD, the second contains LOCUS (both private and public firms), the third contains Compustat firms (public firms), and the last are firms in the Quarterly Financial Report (QFR). The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements.

Figure 17: Comparison of Total Assets Distributions (2010, Manufacturing Sector)




**Notes:** This figure compares the distribution of firm-level total assets in the manufacturing sector across three samples in 2010. The first sample contains firms in LOCUS (both private and public firms), the second contains only Compustat firms (public firms), and the last contains firms in the Quarterly Financial Report (QFR). The distributions are generated using kernel density estimation and the top and bottom tails have been removed to comply with disclosure requirements.

# B Matching Procedure

Orbis and Compustat contain entity name, employer identification number (EIN), city, state and zip code; Compustat additionally contains street address information. LBD records can be linked to the business register, which contains firm name, EIN, street address, city, state and zip code. The LBD/SSEL is linked to Orbis and Compustat separately and annually using a multi-stage probabilistic matching procedure similar to that used in McCue (2003) to construct the Compustat-SSEL bridge that is available through 2005.

In all, there are nine stages to our matching procedure. In the first stage, Orbis and Compustat records that have EIN information are matched to the LBD/SSEL based on this variable. All remaining unmatched records, along with those that do not contain EIN but contain location information, are then matched based on fuzzed entity name, address, city, and exact state and zip code.[31] For Compustat the second stage matches records based on fuzzed name street address, city and exact state. This second stage cannot be implemented for Orbis because street address is unavailable. The third stage matches records based on fuzzed name and city, and

[31]The term fuzzed refers to our use of the DQMATCH procedure implemented in SAS.

exact state and zip code. Stages 4 through 6 rely on different combinations of fuzzed entity name and two location identifiers. Finally, stages 7 through 9 use fuzzed entity name and one location identifier. In contrast to McCue (2003), we do not base any matches solely on fuzzed entity name.

Due to the probabilistic nature of the matching, one Orbis/Compustat record will initially be linked to multiple records in the LBD/SSEL. First, we clean the annual matched data. Each potential match is evaluated based on the similarity in location (zip code, city and state), name, and industry code between the Orbis/Compustat record and its match in the LBD/SSEL. We rely on the Jaro-Winkler distance to measure the similarity between each matched name and city.[32] For each Orbis or Compustat record, only the highest quality match is retained. This first stage of cleaning results in a data set in which each record, corresponding to a firm-year observation, in Orbis/Compustat is matched to just one record in LBD/SSEL.

We further clean our matches to obtain a panel cross-walk between Orbis/Compustat entities and firms in the LBD/SSEL by taking advantage of the information on matches over time. First, if an Orbis/Compustat entity consistently matches with only one LBD/SSEL firm, but a match was not achieved for all the years for which we have records, the LBD/SSEL firm identifier is imputed. Second, if an Orbis/Compustat entity matched to multiple firms over time, we keep the firm(s) that were matched with the strictest criteria. Third, if an Orbis/Compustat entity still matches to multiple firms over time based on the same criteria, we keep the firm(s) with the highest overall match score. One additional imputation is done for Compustat. A key difference between Orbis and Compustat is that the entity name and location variables in Compustat are static over time and represent information provided by the entity in its latest filing. As a result, for Compustat firms if multiple firm matches remain after the previous steps have been implemented, we take the latest match and impute it backwards.

As a final check, we bring in firm employment and age information from the LBD. For records in which we imputed the LBD/SSEL firm due to multiple firm matches over time, we only consider the imputation valid if we observe firm employment or age in the year the imputation was made. We revert to the original firm match if the imputation is considered invalid. After this step is implemented we still have cases where one Orbis/Compustat entity is matched to multiple firms over time. This could be picking up firm-level reorganization

[32]We thank Mark Kutzbach at the U.S. Census Bureau for giving us access to the Jaro-Winkler comparator code.

and/or mergers and acquisitions. In order to ensure that multiple matches are not driven by the probabilistic nature of our matching, we drop cases where an Orbis/Compustat entity matched with more than three LBD firms. Very few observations are dropped by this criteria, and our implicit assumption is that in the 11 years used in our matching we don't expect a firm to go through more than three reorganizations. Finally, we drop cases where a firm matches with more than two entities and the matches are based on fuzzed name and less than three location criteria.

After these steps have been implemented, we end up with two data sets. Our Orbis-LBD/SSEL data which contains nearly 78 percent of underlying Orbis entity-year observations, corresponding to 70 percent of entities in the underlying Orbis data. 76 percent of these matches are based on EIN, while an additional 18 percent are based on name, zip code, city and state. Our Compustat-LBD/SSEL data contains 84 percent of underlying Compustat entity-year observations, corresponding to 79 percent of entities in the underlying Compustat data. The match rate at the firm-level is consistent with the match rate of Compustat firms reported in McCue (2003) once we take into account that none of our matches are made solely on fuzzed name. 75 percent of these matches are based on EIN, while an additional 6 percent are based on name and full address information.

As a final step in constructing LOCUS, we combine Orbis-LBD/SSEL and Compustat-LBD/SSEL matched datasets to ensure that we do not double count any publicly-listed firms that are in both data sets. We begin by matching the two data sets. If a firm appears in both matched data sets, we give preference to the the data source (Orbis or Compustat) with the longest sample period. Since all Compustat financial statements are consolidated, we expect that only one Compustat entity matches to a LBD firm in each year. In a very limited number of cases more than one Compustat entity matches to one LBD firm in a year, and in all of these cases the match is based either on EIN or fuzzed name and three location variables. Because these matches are of high quality, they most likely represent a reorganization. A visual inspection of the balance sheet in these cases leads us to favor summing financial variables across the Compustat entities in the year we observe the reorganization. Orbis entities file unconsolidated financial statements. As a result, we expect that several Orbis entities may match to a single LBD firm in one year. Since we are interested in tracking firm performance over time, we may be concerned about changes in the composition of Orbis entities reporting balance sheets for the same firm over time. To address this concern, we only keep the set of Orbis entities associated with a particular firm that consistently report their balance sheets. The sample from which we draw on for our regression analysis consists of nearly 198,000 unique firms, 97 percent of which are privately held.

# C Conditional Nonlinear Relationships During the GR

The figures in this section are generated by regressing short-term leverage on size, size squared, age, collateral, profitability, labor productivity and industry fixed effects separately for private and listed firms in 2006 and 2009.

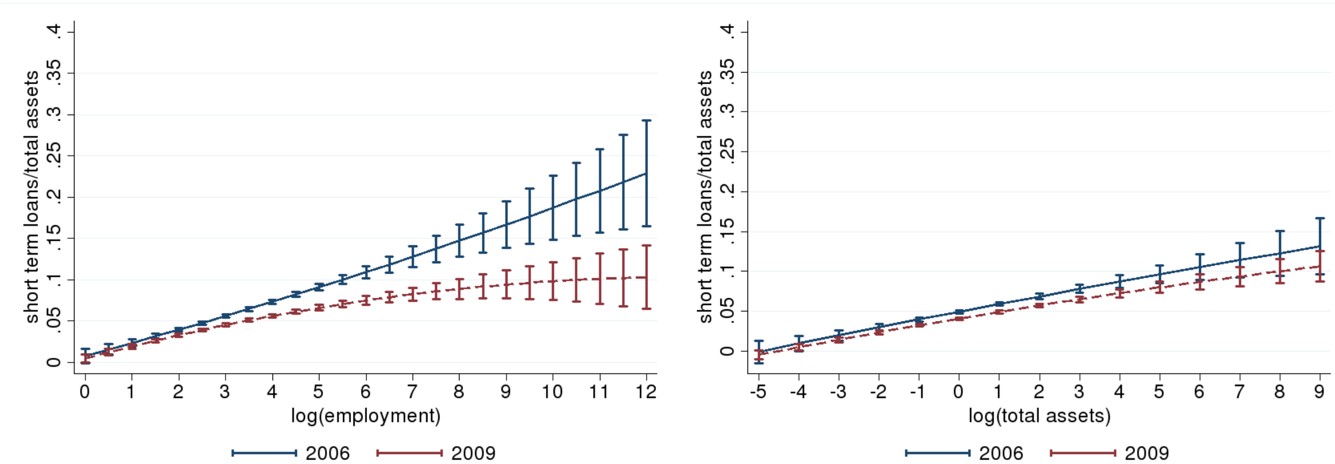
$$\begin{aligned} STLEV_i = &\alpha + \omega_s + \beta_1 \log(SIZE_i) + \beta_2 \log(SIZE_i)^2 + \beta_3 AGE_i + \\ &\beta_4 COLLAT_i + \beta_5 PROFIT_i + \beta_6 PROD_i + \epsilon_i \end{aligned} \tag{13}$$

where $STLEV_i$ is short-term debt over total assets, $\omega_s$ captures industry fixed effects, $SIZE_i$ is measured by either employment or total assets, $AGE_i$ is firm age, $COLLAT_i$ is total fixed assets over total assets, $PROFIT_i$ is net income over total assets, and $PROD_i$ is total employment over revenue.

The results for private firms are reported in figure 18 and for listed firms in figure 19. In both figures, the left panel uses log employment as the measure of size and the right panel uses log total assets.

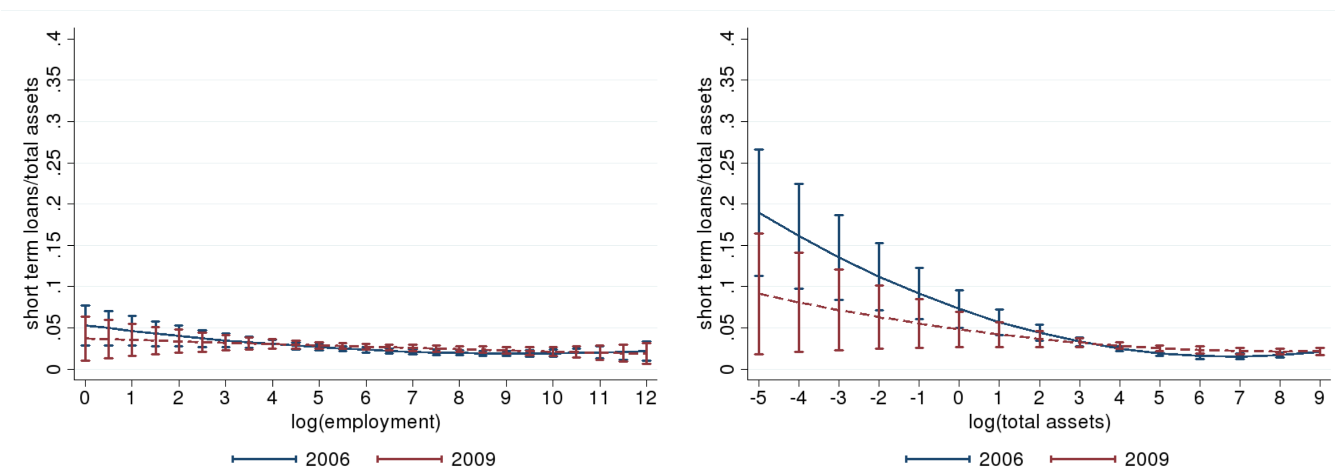
Consistent with our findings in section 4.3, the figures here show a positive relationship between short-term leverage and size among private firms that becomes significantly weaker during the Great Recession when size is measured by employment. In contrast, the relationship between leverage and size is negative among listed firms and we do not find a significant change in the strength of that relationship between 2006 and 2009, regardless of whether size is measured by employment or total assets.

Figure 18: Conditional Relationship between short-term leverage and size for private firms (2006 & 2009)




**Notes:** Use unbalanced sample of private firms separately for 2006 and 2009. The dependent variable is short-term leverage (STLEV). Each line shows the conditional relationship between leverage, size (measured by employment in the left panel and total assets in the right figure), size squared, firm age, collateral, profitability, labor productivity, and a full set of 3-digit industry fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.

Figure 19: Conditional Relationship between short-term leverage and size for public firms (2006 & 2009)




**Notes:** Use unbalanced sample of public firms separately for 2006 and 2009. The dependent variable is short-term leverage (STLEV). Each line shows the conditional relationship between leverage, size (measured by employment in the left panel and total assets in the right figure), size squared, firm age, collateral, profitability, labor productivity, and a full set of 3-digit industry fixed effects. All observations are weighted to adjust for selection into the LOCUS sample.