

Chapter 1

The decline in public firms

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ABSTRACT

Since its peak in 1996, the number of publicly listed US firms has declined by approximately 50%. In addition, US publicly listed firms are now on average larger and older than they were two decades ago. We collect a set of empirical facts on the changes in the distributions as well as entry and exit rates for public and private firms. We develop a model to evaluate which of two mechanisms — an increase in the cost of being public or a shift in the supply of private firm financing — can explain the decline in US public listings and changes in the firm distribution. We calibrate the model to match the data prior to 1996 and then quantify the extent to which these two mechanisms can explain the changes observed in the data.

1 Introduction

Since a peak of approximately 7,500 firms in 1996, the number of US publicly listed firms has decreased by 50% in the last two decades. In contrast, the total number of US firms has steadily increased over this period. With a lower frequency of initial public offerings, fewer young and small firms are going public. The reason for this decline in the propensity of firms to go public, remains an open question.

In this paper, we evaluate two commonly cited explanations for the decline of public firms. The first is an improvement in private capital markets that has reduced the financing costs for private firms. That is, from a financing perspective, the relative benefits of being publicly listed have declined. The second explanation is an increase in the costs of operating as a publicly listed firm, resulting from regulation, disclosure requirements, activist investors, etc. While both explanations amount to a reduction in the net benefit to being public, they entail very different policy implications.

We start by collecting a set of empirical facts on the evolution of public and private firms in the US over the last 40 years. We show that while there has been significant growth in venture capital and private equity funding of young firms, the propensity of these firms to become public has declined. In general, we find evidence consistent with a decline in the net benefits to public listing. Both incumbent public firms as well as firms at their IPO date are larger and older than in previous periods.

We then develop an equilibrium model of the market for private capital in which entrepreneurs endogenously choose to enter and operate as a private firm. Once established, a private firm can pay a fixed cost and become publicly listed. In addition to this fixed cost, a public firm faces a higher ongoing operating cost, reflecting the increased burdens of dealing with regulation, disclosure, and investors. The benefit to public listing is a lower discount rate, resulting in a higher valuation. Thus, in choosing whether to publicly list, a firm trades off fixed costs of an IPO along with ongoing increased costs of operations against a lower cost of capital. The spread between the cost of capital for private and public firms is determined in equilibrium and we solve for the stationary distributions of private and public

firms. We calibrate the model to the data for the period prior to 1996, when the decline in public listing began. Then, we use the model to evaluate the effect of an increase in the ongoing cost of being publicly listed, an increase in the cost of IPO, and an outward shift in the supply of private capital. We show in the model that increased costs of being public and a shift in private capital supply have distinct predictions for the distributions of public and private firms.

Our paper contributes to multiple strands of literature. First and foremost, our work complements recent studies that document the decline in the number of U.S. public firms, the so-called “U.S. listing gap,” and investigate possible explanations for this phenomenon. Gao, Ritter, and Zhu (2013) are among the first to document the number of IPOs dropping more than threefold below the historical average. Doidge, Karolyi, and Stulz (2017) establish that these empirical patterns are novel to the U.S. The number of listings in non-U.S. developed countries, on the contrary, has increased over the same period. They also find that the decline in the number of public listings can be equally explained by a low number of new lists and a high number of delists, majority of which are acquisitions of public firms. Kahle and Stulz (2017) further show that in recent years U.S. public firms have become larger, older, and less profitable; they rely more on R&D investment relative to capital investment. Accordingly, Gao et al. (2013) document that the IPO rate is particularly low among small, young firms. Collectively, these empirical papers point to the possibility that something is amiss in the U.S. public markets.

A common explanation is that the regulatory changes of the early 2000s imposed additional compliance costs on publicly traded firms and made being public less attractive. One prominent example is the Sarbanes-Oxley Act of 2002 (SOX), which made disclosure requirements stricter and increased the administrative costs of preparing accounting statements (e.g., Leuz 2007; Zhang 2007; Engel, Hayes, and Wang 2007; Iliev 2010). However, the increased regulatory hurdles can only partially explain the U.S. listing gap. Kahle and Stulz (2017) note that the drop in public firms predates the regulatory changes, and the fraction of firms that go from public to private is small compared to the fraction of firms exiting public

markets because of merges. More recently, Dambra, Field, and Gustafson (2015) points to the 2012 Jumpstart Our Business Startups (JOBS) Act, which exempts emerging growth companies from certain accounting and disclosure requirements mandated by the SOX, as effective in promoting IPO activity among such companies. This finding is consistent with the regulatory overreach hypothesis being a potential explanation for the listing gap. At the same time, Chaplinsky, Hanley, and Moon (2017) find no evidence of lower direct costs of issue, such as accounting, legal, or underwriting fees, following the Act. On the contrary, they document an increase in indirect costs of going public as measured by the underpricing of the firm's shares at the time of the IPO. Similarly, Barth, Landsman, and Taylor (2017) show larger IPO underpricing for emerging growth companies.

An alternative driver behind the decline in U.S. public listings could be positive changes in the private equity markets. Ewens and Farre-Mensa (2017) provide evidence that the deregulation of securities laws in the 1990s made it easier for firms to raise capital privately. For example, the National Securities Markets Improvement Act of 1996 exempted private sales of securities from state regulations known as blue-sky laws, thereby facilitating private firms' access to a larger set of investors. Late-stage startups benefited the most by being able to finance large funding rounds and raise capital from the out-of-state investors. Davis (2016) further argues that the firms' ability to rent capital or outsource reduces their need to accumulate large amounts of physical assets and, hence, to rely on public markets to secure funding for capital expenditures. Other studies posit that the Internet has reduced the costs of finding investors for private firms and as such public markets no longer offer the benefit of lower search costs relative to private markets (Goldmanis, Hortaçsu, Syverson, and Emre 2010; Gao, Ritter, and Zhu 2013; Doidge, Karolyi, and Stulz 2017; Kahle and Stulz 2017; Doidge, Kahle, Karolyi, and Stulz 2018). The contribution of our paper is to shed light on whether the decline in U.S. public listings is a symptom of a broader issue with public markets or a result of improved conditions in private markets. In this sense, our study is a key step towards informing future economic policies and regulations targeted at promoting IPO activity.

Generally, public ownership of equity allows firms to obtain large scale financing at a cost that is not feasible for a privately owned company. Yet, they must pay a large fixed cost to become a publicly listed firm (Lowry et al. 2017; Doidge et al. 2017) and incur additional ongoing costs stemming from regulatory scrutiny and disclosure requirements (Leuz 2007; Zhang 2007; Engel et al. 2007; Iliev 2010). These benefits and costs are explicitly captured in our model. However, there are a number of other factors that might affect a firm's going-public decision which we do not incorporate in our model. First, companies entering public capital markets face increased visibility. While increased visibility can allow firms to sell their shares at a higher price to public investors as compared to private investors (Chemmanur and Fulghieri 1999), it can also attract additional competition in the product market (Maksimovic and Pichler 2001) and reveal trade secrets Farre-Mensa (2017). Second, there are factors related to acquisitions and control. Zingales (1995) argues that going public makes it easier to find a potential buyer to acquire the firm. Others argue the reverse, that firms conduct an IPO in order to more easily acquire other firms (Brau and Fawcett 2006; Celikyurt, Sevilir, and Shivdasani 2010). On a different note, firms may choose to go public in order to divert ownership away from venture capitalists and re-establish the control (Black and Gilson 1998).

More broadly, this paper is related to other theoretical studies analyzing the economic factors underlying a firm's decision to go public. One view is that going public serves as an opportunity for an entrepreneur who wishes to sell his firm. Bayar and Chemmanur (2011) study a private firm's choice between conducting an IPO and exiting private markets through an acquisition by another firm. Zingales (1995) shows that going public before selling a firm to an interested buyer increases the sale's proceeds. Another view is that going public is attractive because of liquidity and diversification benefits, yet involves giving up advantages of being private. Pástor, Taylor, and Veronesi (2008) and Boot, Gopalan, and Thakor (2006) argue that it is easier to maintain control of a firm under private ownership. Going public can also incur increased information production costs (Chemmanur and Fulghieri 1999) or signal a new technology's viability to potential entrants and encourage product market competition

(Maksimovic and Pichler 2001). Pástor and Veronesi (2005) emphasize the role of changing market conditions for IPO decisions and focus on rationalizing IPO waves. In contrast to these studies, we develop a real option model which allows us not only to assess the key trade-offs to a company being publicly versus privately owned quantitatively, but also to characterize the shifts in the cross-sectional distribution of public and private firms. Our analysis builds upon the real option model presented in Dixit and Pindyck (1994) and, therefore, is methodologically similar to other studies using these tools, though topically different (Miao 2005; Luttmer 2007; Hartman-Glaser, Lustig, and Xiaolan 2019).

The rest of the paper is organized as follows. Section 2 discusses the data and provides key empirical facts. In Section 3 we set up an economic model to interpret the empirical evidence. In Section 4 we describe the main model mechanisms and in Section 5 we assess them quantitatively, followed by the Conclusion and Appendix.

2 Data and Empirical Results

To measure the number of publicly listed firms in the U.S., we use the Center for Research in Security Prices (CRSP) Monthly Stock File and follow the definition of Doidge et al. (2017). Specifically, we include all U.S. domiciled common stocks (share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ stock exchanges (exchange codes 1, 2, and 3), except the investment funds and trusts (SIC codes 6722, 6726, 6798, and 6799).¹ We keep only December observations to identify whether a company satisfies the above criteria in a given year. Our benchmark sample covers the period from 1980 until 2018.

To understand how public firms have changed over the sample period, we merge our CRSP dataset with the Standard & Poor's Compustat Annual. When examining the public

¹However, in contrast to Doidge et al. (2017) we do not exclude a company in a given year from the firms count if it does not satisfy the above criteria temporarily. For example, consider a firm that goes public in year t and immediately has its equity shares traded on Amex. In year $t+10$ the firm's shares are temporarily delisted from the exchange, but in year $t+12$ the shares are again traded up until the firm exits. In our measure, we count this firm towards our measure in all years between its IPO date (or the first trading date) and exit date as long as it satisfies the criteria of Doidge et al. (2017) at least in one year. Nonetheless, both measures are very similar quantitatively.

firms characteristics, we use the intersection of CRSP and Compustat firms.² The dataset provides firms' total revenues (*sale*), total earnings (*oibdp*), total book assets (*at*), debt in current liabilities (*dlcc*), long-term debt (*dlt*), and number of employees (*emp*)³. For some firms, Compustat reports financial data few years prior to the initial public offering. Backfilled data can bias upward the number of publicly listed firms. To tackle this issue, we use the offer dates for firms going public collected by Jay R. Ritter and exclude observations prior to the firm's offer date. For the listed firms that are not in the Ritter dataset we assign the first trading day as the offer date.⁴ Moreover, we use the Ritter founding dates to construct firm age.

The biggest challenge when measuring the number of private firms in the U.S. is the lack of comprehensive data tracking the U.S. private sector. Another challenge is identifying a set of private firms that are very likely to consider whether to go public or stay private. That said, we use three alternative measures for private firms counts to establish our main empirical findings.

First, we consider all companies backed with financing from venture capital (VC) and private equity (PE) funds in the Thomson Reuters VentureXpert database. All firms that have raised at least one round of financing after 1980 are included.⁵ The sample includes 52,941 unique portfolio companies. The two main types of financing instruments are VC equity investment and convertible preferred stock. They constitute approximately 43% and 24% of all investments, respectively. Importantly, the VentureXpert dataset provides the amount of capital raised at each financing round.

Focusing on VC/PE-backed private firms offers a number of advantages. First, we are able to directly measure the flow of capital into the private sector. Second, the prevalence of the VC-financed firms among the publicly traded firms allows us better to identify a set

²Firms that are listed on CRSP but not covered by Compustat account for less than 3% of the aggregate market capitalization of all listed firms (see Kahle and Stulz (2017)).

³We replace *sale*, *at*, *dlcc*, *dlt*, and *emp* with a missing value when they are less than or equal to zero.

⁴For companies with multiple securities (*permno*), we use the first trading day of a security which is listed on an exchange earlier.

⁵We exclude firms receiving leveraged buyout financing from our analysis.

of private firms that are likely to go public in their life cycle. Even though only 0.1% of all privately-held firms ever received venture capital funding (Puri and Zarutskie 2012), in our sample VC/PE-backed firms account for over 36% of all IPOs over the period 1980-2018.⁶ Finally, we are also able to analyze the entry rates of the private firms into the public markets through an acquisition by a public firm rather than through an IPO. Therefore, we focus on the number of VC/PE-backed companies as our baseline count of private firms in the U.S. By no means, this measure captures all potential entrants in the public equity markets.

To construct the number of VC/PE-backed companies, we rely on the firms' founding dates reported by the VenturExpert. For the firms with no reported founding date, we assign the date of the first financing round as the birth date (around 30% of all firms in our analysis sample). We track firms from their entry year to the year of their first exit event or until 2018 when our sample ends. A private firm can exit either by going public, being acquired by another firm, or failing. The VenturExpert does not provide a comprehensive data on the firms' exit dates. We merge the CRSP dataset with the VenturExpert using name and address matching to identify the IPO dates for the VC/PE-backed firms. Appendix A.1 contains a detailed description of how we match the two databases. Further, we merge the Thomson Reuters SDC Platinum Mergers and Acquisitions database to the VenturExpert using the deal numbers. This merge allows us to identify firms exiting private markets via an acquisition (i.e., acquisition targets) along with their exit dates.⁷ For firms without a successful exit – either via an IPO or acquisition, we impute failure dates based on the last round of financing: if a firm has not raised any financing for five years since its last round, we classify it as being shut down. This assumption is on the conservative side, since an average gap between the two consecutive financing rounds for a VC/PE-financed is less than 2 years. For robustness, we show that changing the failure date to 3,4,6, or 7 years from the last financing round does not produce a large quantitative impact on our results.

To corroborate our benchmark empirical findings, we also consider alternative measures

⁶This number is comparable to the numbers documented by Ritter (2017).

⁷Since SDC Platinum M&A database has a greater coverage of larger acquisitions and acquisitions by public acquirers, an exit event for some firms could be missclassified (see e.g., Puri and Zarutskie (2012)).

of the number of private firms. Specifically, we use business tax statistics prepared by the Internal Revenue Services (IRS). The IRS provides balance sheet, income statement, and other selected financial data for all active corporations filing Form 1120 from 1964 until 2015. The data are available at the aggregate level and for the subsets of firms classified by the size of business receipts and total assets. To better capture a set of potential public market entrants, we restrict our attention to sufficiently large private firms, since these are the firms with the resources necessary to go public and maintain a public listing. In particular, we focus on firms with total assets above \$50m and \$100m, and with revenues above \$50m.

The key downside of measuring the number of private firms using the IRS data is that corporations are classified into size groups based on nominal rather than real cutoff values for business receipts and total assets, making it difficult to compare private firms' counts and characteristics across years. For instance, we can observe the growth in the number of firms with the nominal total assets above \$50m, even if the number of large firms with the revenues above the corresponding real cutoff values remains constant. Such growth would be purely driven by inflation, rather than by growth of large businesses. To address these inflation concerns, we also construct the number of firms with the real total assets above \$50m by linearly extrapolating the data within each size bucket.

Finally, we complement our analysis with firm counts from the U.S. Census Bureau based on the number of employees. Specifically, we focus on firms with more than 500 employees. Importantly, these counts are not subject to inflation issues.

In addition to firms' financial data, we also use data on CPI inflation from the Bureau of Labor Statistics. The price level is normalized to 1 in December of 2009. All nominal quantities are deflated by the CPI to obtain real measures.

Propensity to go public. In this section, we revisit the evolution of U.S. public listings over the past few decades. Figure 1 shows that the number of public firms has increased rather steadily from 1980 until 1996 and then decreased almost twofold since 1996. In their paper, Doidge et al. (2017) document that this dramatic decline is unique to the United

States and has not arisen in the rest of the world, constituting the so-called U.S. listing gap. We also find that this pattern is present for publicly listed firms that have received VE/PE financing. Specifically, the number of VC/PE-backed firms drops on average by 35% between the periods 1994–1998 and 2011–2015 (see Table 1).

Admittedly, the size of the public market as measured with the aggregate market value of public firms has not shrunk over our sample period. It has increased dramatically from \$10 trillion in 1980 to \$25 trillion in 1999, thereafter experiencing two large drops during the dot-com crash and the recent financial crises. Nonetheless, the size of the public market remains significantly larger in the post-1996 period as compared to the pre-1996 period. This is in line with the evidence that mostly small public firms have been disappearing in the recent two decades.

We further investigate whether this decline is specific to publicly listed firms or applies to private ones as well. To this end, we construct the firm propensity to go public over time, defined as the ratio of the number of public firms to the number of private firms. Note that if the decrease in the number of public firms coincides with a corresponding decrease in the number of private firms, this ratio would remain constant. Instead, Panel B of Figure 1 displays substantial growth in the number of VC/PE-backed private firms over the period from 1980 until 2018. This finding is further supported by Figure 2 which shows that both the number of new private firms receiving financing from VC/PE funds and the amount of received capital are trending upwards over the sample period. The steady increase in the number of private firms rules out the possibility that the decrease in the number of public firms is the product of a widespread downwards trend in the number of potential public market entrants. Accordingly, due to the number of public and private firms moving in opposite directions, we observe a steady decline in the firm's propensity to go public (see Panel C of Figure 1). The trend is quite similar regardless of whether we consider the set of all publicly traded firms or restrict attention only to VC/PE-backed public firms.

For robustness, we consider alternative measures of the number of private firms: the number of private firms with more than 500 employees, the number of private S&C-corporations

with with total assets above \$50m and \$100m, and with revenues above \$50m. Moreover, we recalculate the number of VC/PE-financed firms when the failure date is set to 3,4,6, and 7 years from the last financing round if a firm has not exited earlier via an IPO or acquisition. We again find a downward trend in the firm’s propensity to go public over the period of interest (see Appendix Figure B.1 and Table B.1). Across all measures, the firm’s propensity to go public has decreased by 50-70% over the period from 1996 until 2015.

The decline in the number of public listing in the U.S. may have resulted either from a decline in the IPO rate or from an increase in the exit rate. Figure 3 plots the number of IPOs and IPO rate over time. The latter is calculated as the ratio of the number of IPOs to the number of private firms. The IPO rate declines from about 6% in 1996 to 1% in 2018, indicating that the decline in the number of public firms can be to a great extent explained by the decline in the IPO rate. Again, we find that this pattern also holds for a subset of VC/PE-backed private firms choosing to go public.

An alternative driving force of the U.S. listing gap could be an increased number of exits among public firms. Panel A of Figure 4 depicts the number of public firms that have delisted from a stock exchange either voluntarily or involuntarily. As can be seen from the figure, the number of exits has been fluctuating between 200 and 500 firms per year in the pre-1996 period. However, it has increased dramatically thereafter, reaching its peak of 875 in 1998 and then reverting back to near the pre-1996 values. This large increase in firm exits in the late '90s and early '00s has contributed to the decline in the number of public listings. At the same time, historically low number of exits since 2002 cannot solely explain a further drop in the propensity to go public. We also plot the number of exits scaled by the total number of public firms, i.e. the exit rate (see Panel B of Figure 4). The dynamics of the exit rate follow very closely the dynamics of the raw number of firm exits. If we focus only on VC/PE-backed firms we find quite similar dynamics over time, though the exit rate is relatively higher in the latter period as compared to the pre-1996 period.

We further examine the delisted firms by decomposing the exit rate depending on a reason for the exit. First, we examine delists for “negative” reasons (e.g. company liquidation or

bankruptcy), defined as securities with delisting codes $4xx$ and $5xx$ (excluding “gone private” exits with the delisting code 573). Panel D demonstrates that the exit rate for “negative” delists has been fluctuating mostly between 2% and 5% both for all public firms and for VC/PE-backed firms, without exhibiting any secular trends. Second, we examine exits through mergers and acquisitions, defined as securities with delisting codes $2xx$ and $3xx$. Panel F demonstrates that the exit rate for mergers and acquisitions fluctuates between 2% and 6%, with sharp increase in the early '90s until 2000, dip in 2001, and end value around the 1996 rate. Again, for VC/PE-backed firms the exit rate is slightly higher in the recent years as compared to the 1996 level.

We also analyze how frequently public firms re-exit the private markets. The CRSP records such exit events with the delisting code 573. Panel A of Appendix Figure B.2 shows that the number of such exits is negligible. Alternatively, a public firm can go private via an acquisition by a private firm, in which case the delisting code is either $2xx$ or $3xx$. To identify public firms re-exiting the private markets, we merge the SDC Platinum M&A database to the CRSP and count the number of deals with a public target and non-public acquirer.⁸ More details on the merge are provided in Appendix A.2. Panel C of Appendix Figure B.2 demonstrates that the number of public firms going private via an acquisition fluctuates between 50 and 150, with a large spike before the dot-com bubble. In order to preserve model tractability, we do not incorporate that a firm has an option to go back private after conducting an IPO.

Size distribution of public firms. Over our sample period, there has been a significant shift in the distribution of publicly listed U.S. firms. We find that over the last few decades the typical public firm has become larger. As shown in Figure 5, the average size of public firms as measured with the market firm value has increased more than twofold from about \$3b in 1996 to \$8b in 2018. We document similar secular trends when calculating the median firm size or when measuring the firm size with total book assets, market equity value, revenues, earnings, age, or number of employees (see Appendix Figures B.8, B.9 and

⁸We classify a firm to be *public* if it satisfies the criteria in Doidge et al. (2017) in at least one year between its IPO date (or the first trading date) and exit date.

Table B.3). Again, our findings continue to hold for a subset of VC/PE-financed public firms.

Figure 6 further supports that the right tail of the public firm size distribution has increased in mass in the recent two decades. The Figure depicts the power law exponent γ , which is given by the solution to the equation $Pr(size > X) = kX^{-\gamma}$ for some constant k . When measuring the size with total book assets, the estimates of the power law exponent coefficient fluctuate around 1.2-1.3 from 1980 till 1990, sharply decline to 1 thereafter, and only increase to 1.1 from 2010 onward. The secular trend in the power law coefficient is qualitatively similar if we measure the firm's size with revenues, though the sharp drop in the coefficient occurs only in mid 2000s.

Firm characteristics at IPO. Not only does the typical public firm becomes larger in the recent years, but so does the typical firm that goes public. As shown in Panel A of Figure 7, firm size at IPO year increases almost threefold from prior to the decline in public firms to the end of the sample. This finding continues to hold if we measure the firm's size with total book assets, market equity value, revenues, earnings, age, or number of employees (see Appendix Figure B.10, B.11 and Table B.3). We find very similar dynamic of the firm's size at IPO year for firms receiving funding from VC/PE funds.

A larger size threshold needed to IPO could be indicative of a lower net benefit of going public, but likely not if the underlying reason is a shift to the right in the firm size distribution. As such, we investigate by how much firm size at IPO year has changed relative to other public firms. Specifically, we identify the percentile of median firm size at IPO year within the distribution of public firms. As shown in Panel A of Figure 8, both in the beginning and end of the sample firms conducting IPOs are larger than 30-40% of public firms, with the exception of late '90s when this ratio increases to 60%. We find similar patterns when measuring firm size using firms' market value and total book assets. This behavior suggests that the firms conducting IPOs are not larger relative to existing public firms.

Changes around IPO. Next, we explore changes in firms' characteristics such as capital stock and profitability around the IPO date. To measure changes in each variable of interest,

we follow the approach in Davis, Haltiwanger, and Schuh (1996) and compute the growth rates using the following formula:

$$\Delta x_{j,t} = \frac{x_{j,t+1} - x_{j,t-1}}{0.5(|x_{j,t+1}| + |x_{j,t-1}|)},$$

where t is the year of an IPO. The growth rates are between the post- and pre-IPO values of x . This approach allows us to mitigate the effect of outliers, as well as account for possible negative values of x .

First, we examine the changes in firms' capital stock, which is measured with net property, plant, and equipment (*ppent*). We rely on the backfilled data from the Compustat when measuring firms' characteristics one year prior to an IPO. Panel A of Figure 9 demonstrates that firms' capital increases by 40% – 80% on average following an IPO. This finding is consistent with the existence of a positive premium on cost of capital for private firms over that for public firms. If the cost of capital decreases once a firm goes public, we would expect firms to increase their capital investment after an IPO. The figure also shows that there is a regime shift around 2000: the capital growth rate fluctuates around 70% in the early period of our sample and drops to approximately 50% in the late period of the sample. This drop over time suggests a decrease in the premium on cost of capital for private firms. If we focus on VC/PE-backed firms, we find very similar patterns over time, though the post IPO increase in capital is on average 5-10% higher as compared to all public firms.

Second, we examine changes in firms' profitability around the IPO date. We measure firms' profitability as a ratio of operating income before depreciation (*oibdp*) and total book assets (*at*). Similarly to Pástor, Taylor, and Veronesi (2008), we find that firms' profitability drops after an IPO. This finding is in line with firms operating decreasing returns to scale technology and scaling up their capital after going public. Further, we find that this drop in profitability disappears in the recent two decades (see Panel B of Figure 9). For VC/PE-financed firms, we find no drop in profitability around the IPO date in the early period of sample and an increase in the late period of the sample.

3 Model

In this section we describe the model setup and derive valuations for private and public firms. We then characterize the distributions of public and private firms and the stationary equilibrium.

Time is continuous and the horizon is infinite. The economy is populated with a continuum of firms, consisting of two types: public and private. All firms initially enter as private and can subsequently choose to become public by paying a fixed cost. We focus on two main features that drive the decision to go public. First, we assume that public firms have a lower cost of capital than private firms. Investors in our model are risk-neutral but this difference in the discount rate can be thought of as an illiquidity premium for private firms. Second, there are operational costs associated with being publicly listed. We model these as consisting of both a one-time sunk cost, incurred at the time the firm decides to go public, as well as an ongoing fixed cost of operations. These costs are intended to capture the additional regulatory, disclosure, and compliance costs associated with being a publicly listed firm.

3.1 Firm cash flows

Firms produce using capital, k , which is rented and can be flexibly adjusted and are subject to idiosyncratic productivity shocks, x . All firms face a common corporate tax rate τ and a fixed operating cost c_f . Investors are risk-neutral and apply a premium, θ , to the discount rate for private firms. A private firm's after-tax profits are given by

$$\pi_{priv}(x; \theta) = \max_k (1 - \tau)(xk^\alpha - \delta k - c_f) - (r + \theta)k, \quad (1)$$

A firm's productivity, x , evolves as

$$\frac{dx_t}{x_t} = \mu dt + \sigma dw_t - dJ_t, \quad (2)$$

where w_t is a standard Brownian motion and J_t is a Poisson process with arrival intensity λ . The optimal investment rule satisfies,

$$(1 - \tau)(\alpha x k^{\alpha-1} - \delta) = r + \theta \quad (3)$$

which gives

$$k_{priv}^*(x; \theta) = \left(\frac{\alpha x}{\frac{r+\theta}{1-\tau} + \delta} \right)^{\frac{1}{1-\alpha}}. \quad (4)$$

Plugging this back in, we can write after-tax private firm profits as

$$\pi_{priv}(x) = (1 - \tau)(\mathcal{A}_{priv}(\theta)x^{\frac{1}{1-\alpha}} - c_f), \quad (5)$$

where

$$\mathcal{A}_{priv}(\theta) = (1 - \alpha) \left(\frac{\alpha}{\frac{r+\theta}{1-\tau} + \delta} \right)^{\frac{\alpha}{1-\alpha}}. \quad (6)$$

Given the presence of the fixed operating cost, c_f , a private firm will choose to optimally shut down when productivity falls to a sufficiently low value. We assume a zero recovery rate in the event of exit. We will use T_{Dpriv} , to denote the private firm's optimal stopping time that it chooses to shut down. This optimal stopping decision can be expressed a lower threshold on the private firm productivity, which we will denote by $x_{D,priv}$.

A private firm can also decide to undertake an IPO to become a public firm. To become public, a firm must pay a one-time cost of \mathcal{I}_{IPO} . The benefit to becoming public is that a firm faces a lower cost of capital. Specifically, public firms avoid the illiquidity premium, θ , that investors apply to private firms. However, public firms are also subject to additional costs, both in the form of a one-time fixed cost at the time of IPO, \mathcal{I}_{IPO} , as well as an ongoing flow cost, \mathcal{C}_{pub} .

Public firm cash flows are similar to those of private firms, however public firms face a lower opportunity cost of capital (r instead of $r + \theta$) and an additional cost to being public, \mathcal{C}_{pub} . Public firm after-tax profits are given by

$$\pi_{pub}(x) = \max_k (1 - \tau)(xk^\alpha - \delta k - c_f) - rk - \mathcal{C}_{pub}. \quad (7)$$

Public firms' optimal capital choice is

$$k_{pub}^*(x) = \left(\frac{\alpha x}{\frac{r}{1-\tau} + \delta} \right)^{\frac{1}{1-\alpha}} \quad (8)$$

Plugging in, we can write public firm profits as

$$\pi_{pub} = (1 - \tau) \left(\mathcal{A}_{pub} x^{\frac{1}{1-\alpha}} - c_f - \frac{\mathcal{C}_{pub}}{1 - \tau} \right), \quad (9)$$

where

$$\mathcal{A}_{pub} = (1 - \alpha) \left(\frac{\alpha}{\frac{r}{1-\tau} + \delta} \right)^{\frac{\alpha}{1-\alpha}}. \quad (10)$$

3.2 Firm valuation

The private firm's problem amounts to choosing capital, k , a stopping time for exit, T_{Dpriv} , and a stopping time for the IPO, T_{IPO} . For a private firm with current productivity, x , its value can be expressed as

$$\begin{aligned} v_{priv}(x; \theta) = & \sup_{\{k_t\}_{t \geq 0}, T_{Dpriv}, T_{IPO}} \mathbb{E} \int_0^{T_{Dpriv} \wedge T_{IPO}} e^{-(r+\lambda+\theta)t} \pi_{priv}(x_t; \theta) dt \\ & + e^{-(r+\lambda+\theta)T_{IPO}} \mathbb{1}_{[T_{IPO} < T_{Dpriv}]} \left(v_{pub}(x_{T_{IPO}}) - \mathcal{I}_{IPO} \right), \end{aligned} \quad (11)$$

where $T_{Dpriv} \wedge T_{IPO} \equiv \inf\{T_{Dpriv}, T_{IPO}\}$. The first integral reflects the present discounted value of the private firm's cash flows until the time that it chooses to exit (T_{Dpriv}) or go public (T_{IPO}). In the event of exit, the firm receives a zero payoff. The second term reflects the payoff at IPO.

The public firm's problem is to choose optimal capital, k , and a stopping time, T_{Dpub} , at which it optimally shuts down. In the event of shut down, we assume that a public firm receives a final payoff of zero. The public firm chooses capital, k , and a stopping time at which it optimally exits, T_{Dpub} . A public firm's value, for a given level of current productivity x , is given by

$$v_{pub}(x) = \sup_{\{k_t\}_{t \geq 0}, T_{Dpub}} \mathbb{E} \int_0^{T_{Dpub}} e^{-(r+\lambda)t} \pi_{pub}(x_t) dt \quad (12)$$

The public firm value is the expected discounted value of the future after-tax cash flows until the time of exit, which occurs either because the firm's productivity falls sufficiently low or because the firm is hit with an obsolescence shock.

Proposition 1. Define $b \equiv \frac{1}{1-\alpha}$ and assume

$$r + \lambda - \mu b - \frac{\sigma^2}{2}b(b-1) > 0.$$

The value of a private firm with current productivity x is given by

$$v_{priv}(x; \theta) = A_1 x^{\gamma_1} + A_2 x^{\gamma_2} + (1 - \tau) \left(\frac{\mathcal{A}_{priv}(\theta) x^b}{r + \theta + \lambda - \mu b - \frac{\sigma^2}{2}b(b-1)} - \frac{c_f}{r + \theta + \lambda} \right), \quad (13)$$

where the coefficients A_1 and A_2 are solved for by imposing the boundary conditions and \mathcal{A}_{priv} is defined in Equation (6). The value of a public firm value is given by

$$v_{pub}(x) = B_2 x^{\xi_2} + (1 - \tau) \left(\frac{\mathcal{A}_{pub} x^b}{r + \lambda - \mu b - \frac{\sigma^2}{2}b(b-1)} - \frac{c_f}{r + \lambda} - \frac{C_{pub}}{(1 - \tau)(r + \lambda)} \right), \quad (14)$$

where the B_2 coefficient is solved for by imposing the boundary conditions and \mathcal{A}_{pub} is defined in Equation (10).

3.3 Private firm entry

There is an exogenous flow M of new entrepreneurs that draw a startup cost c_e from the cumulative distribution function $F(c_e)$. We assume this entry cost is lognormally distributed:

$$\log(c_e) \sim \mathcal{N} \left(\log(\bar{c}_e) - \frac{1}{2}\sigma_{ce}^2, \sigma_{ce}^2 \right). \quad (15)$$

As noted in Gourio and Roys (2014), the variance of the entry cost, σ_{ce}^2 , parameterizes the inverse elasticity of the supply of private entrants. Having observed their drawn entry cost, c_e , an entrepreneur can then choose whether to pay this cost and begin operating as a private firm. Otherwise, the entrepreneur simply exits at zero cost. We assume the entry decision must be made immediately and cannot be delayed. The initial productivity at entry, x_0 , is drawn from a uniform distribution with support over the interval $[x_A, x_B]$. Given θ , a firm will choose to enter if their expected value upon entering is greater than or equal to the startup cost drawn:

$$\int_{x_A}^{x_B} \frac{v_{priv}(x; \theta)}{x_B - x_A} dx \geq c_e. \quad (16)$$

Let $c_e^*(\theta)$ denote the maximum drawn entry cost such that an entrepreneur would pay the cost and enter. That is, $c_e^*(\theta)$ is such that Equation (16) holds with equality. The endogenous flow of new private firms entering, $N(\theta)$, is given by

$$N(\theta) = F(c_e^*(\theta))M, \quad (17)$$

In what follows, we will write the flow of new private entering firms simply as N , suppressing the dependence on θ . For a given level of productivity x , the value of a private firm is decreasing in θ . Intuitively, for a higher level of θ , a private firm's future cash flows are subject to a higher discount rate and therefore have a lower valuation. Thus, $c_e^*(\theta)$ and the flow of new private firms, N , are both decreasing in θ .

3.4 Distribution of private firms

We now characterize the stationary distribution of private firms. In the stationary equilibrium, the masses and aggregate variables for public and private firms are constant, though individual firms enter, exit, and experience heterogeneous productivity shocks.

Private firms choose to optimally shut down when the productivity falls to $x_{D,priv}$ and optimally choose to go public when productivity reaches \bar{x}_{IPO} . As a result, the distribution of private firm productivity, x , has support over the interval $(x_{D,priv}, \bar{x}_{IPO})$. There is an endogenous flow N of new private firms that enter with productivity uniformly distributed over the interval $[x_A, x_B]$. Private firms exit the distribution for one of three reasons: they reach the optimal exit threshold $x_{D,priv}$, the IPO threshold \bar{x}_{IPO} , or are hit with an exogenous death shock. In the stationary distribution, the total entry and exit flows are equal.

We divide the private firm distribution into three regions: $(x_{D,priv}, x_A)$, $[x_A, x_B]$, (x_B, \bar{x}_{IPO}) . In the first and third region, there is no firm entry, while in the middle region there is a flow N of new private firm entrants.

Proposition 2. *The stationary distribution of private firm productivity is $N \times \varphi(x)$, where*

N is defined in Equation (17) and

$$\varphi(x) = \begin{cases} C_1 x^{\beta_1-1} + C_2 x^{\beta_2-1}, & \text{if } x_{D,priv} < x < x_A \\ D_1 x^{\beta_1-1} + D_2 x^{\beta_2-1} + \frac{1}{(x_B-x_A)(\lambda+\mu-\sigma^2)}, & \text{if } x_A \leq x \leq x_B \\ H_1 x^{\beta_1-1} + H_2 x^{\beta_2-1}, & \text{if } x_B < x < \bar{x}_{IPO}. \end{cases} \quad (18)$$

The coefficients $C_1, C_2, D_1, D_2, H_1, H_2$ are solved by imposing boundary conditions and where

$$\beta_1 = \frac{\mu}{\sigma^2} - \frac{1}{2} + \frac{\sqrt{2\lambda\sigma^2 + (\mu - \sigma^2/2)^2}}{\sigma^2}, \quad \beta_2 = \frac{\mu}{\sigma^2} - \frac{1}{2} - \frac{\sqrt{2\lambda\sigma^2 + (\mu - \sigma^2/2)^2}}{\sigma^2}. \quad (19)$$

3.5 Distribution of public firms

Given the distribution of private firms, we can determine the flow of IPOs, which will effectively act as a scaling factor on the public firm distribution. Let Υ_{IPO} denote the steady state flow of IPOs. Given the distribution of private firms, the flow rate of IPOs can be computed as

$$\Upsilon_{IPO} = -\frac{1}{2}\sigma^2 N \left(\beta_1 H_1 \bar{x}_{IPO}^{\beta_1} + \beta_2 H_2 \bar{x}_{IPO}^{\beta_2} \right). \quad (20)$$

In steady state, there is a flow Υ_{IPO} of firms becoming public, each entering the public firm distribution with productivity \bar{x}_{IPO} . Upon becoming public, the firm's cash flows then evolve according to the previously specified cash flow dynamics for a public firm. Public firms exit for two reasons: they optimally shut down when their cash flows drop to $x_{D,pub}$ or they are hit by an obsolescence shock. Thus, the distribution of public firms has support $(x_{D,pub}, \infty)$. We divide the support into two regions: $(x_{D,pub}, \bar{x}_{IPO})$ and $[\bar{x}_{IPO}, \infty)$.

Proposition 3. *Assume $\lambda + \mu - \sigma^2 > 0$ and $\zeta_2 + \frac{1}{1-\alpha} > 0$. Then the distribution of public firm productivity is given by $\Upsilon_{IPO} \times \Psi(x)$, where*

$$\Psi(x) = \begin{cases} J_1 x^{\zeta_1-1} + J_2 x^{\zeta_2-1}, & \text{if } x_{D,pub} < x < \bar{x}_{IPO} \\ K_2 x^{\zeta_2-1}, & \text{if } x \geq \bar{x}_{IPO}. \end{cases} \quad (21)$$

The coefficients J_1, J_2, K_2 are solved by imposing the boundary conditions and

$$\zeta_1 = \frac{\mu}{\sigma^2} - \frac{1}{2} + \frac{\sqrt{2\lambda\sigma^2 + (\mu - \sigma^2/2)^2}}{\sigma^2}, \quad \zeta_2 = \frac{\mu}{\sigma^2} - \frac{1}{2} - \frac{\sqrt{2\lambda\sigma^2 + (\mu - \sigma^2/2)^2}}{\sigma^2}. \quad (22)$$

Figure 10 displays the stationary distributions of private (blue line) and public (red line) firm productivity. Equation (21) shows that the right tail of public firm productivity exhibits a power law.

3.6 Private capital market

We assume that there is a perfectly elastic supply of private capital, which has an illiquidity premium θ relative to public firm capital. For a given θ , the aggregate private capital is given by

$$K_{priv} = N \int_{x_{D,priv}}^{\bar{x}_{IPO}} k_{priv}^*(x; \theta) \varphi(x) dx. \quad (23)$$

In Figure 11, we plot the supply and demand curves for private firm capital. The solid red and blue lines show the supply and demand curves, respectively, for private capital. The dashed red line represents a case of a reduction in θ , which leads to a larger quantity of aggregate private capital in equilibrium. The blue dashed line represents an increase in the demand for private capital, resulting from an increase in the costs to public firms (\mathcal{I}_{IPO} or C_{pub}).

4 Model mechanisms

In this section we illustrate the effects of three different changes in model parameters: the cost of being public (C_{pub}), the IPO cost (\mathcal{I}_{IPO}), and the premium on private firm financing (θ).

4.1 Costs of being public (C_{pub})

In Figure 12 we show comparative statics for the effect of a change in C_{pub} , a public firm's ongoing operating costs. From Equation (8) we see that C_{pub} does not affect a public firm's optimal investment decision. An increase in C_{pub} does reduce public firm profits and value for a given level of productivity, x . This reduction in value makes it less attractive to be public firm, which increases \bar{x}_{IPO} , the productivity threshold at which a private firm decides

to go public. It also has the effect of increasing $x_{D,pub}$, the threshold at which a public firm optimally chooses to shut down. These increases effectively shift the public firm distribution to the right. Similarly, the profits and value of a firm at IPO are larger for higher levels of the cost of being public. Due to this selection effect, the average productivity, capital, and market value of public firms actually increase with an increase in C_{pub} . The increase in public firm operating costs reduces the average profitability among public firms. While this is somewhat offset by the increase in average public firm size, which has a positive effect on average profitability, the net effect is that a higher C_{pub} results in a lower average public firm profitability.

An increase in the operating costs for public firms also impacts the private firm distribution. The increase in the IPO threshold, \bar{x}_{IPO} , results in private firms delaying their IPO and becoming larger. That is, it extends the right tail of the private firm distribution and reduces the frequency of IPOs. Effectively, an increase in C_{pub} produces an outward shift in the demand for private firm capital. This increases the aggregate private capital in equilibrium. The higher premium on private capital results in private firms choosing to shut down sooner. That is, the minimum private productivity, $x_{D,priv}$, increases.

The increase in C_{pub} also results in less private firm entry. The value of a private firm incorporates the option to become a public firm, as shown in the private firm's problem in Equation (11). Thus, the reduction in the value to being public also reduces a private firm's value. For a potential entrant, this makes the value of entering lower, all else equal.

4.2 Cost of IPO (\mathcal{I}_{IPO})

In Figure 13, we show the effects of changes in the IPO cost, \mathcal{I}_{IPO} . An increase in \mathcal{I}_{IPO} makes it more costly for a firm to become public, however this cost is sunk once a firm is public and therefore has no effect on a public firm's ongoing operations. That is, \mathcal{I}_{IPO} doesn't change a public firm's profits, value, or investment, for a given level of productivity x . It also has no effect on the threshold at which a public firm exits. However, an increase in the IPO cost will push up the threshold for the going public decision, \bar{x}_{IPO} , which reduces

the frequency of IPOs. Additionally, the higher IPO threshold results in a selection effect that impacts the distribution of public firms. With the higher IPO threshold, firms are larger at the time of their IPO. This results in a larger average firm size and a higher average profitability among public firms.

An increase in the cost of becoming public also impacts the distribution of private firms. Firms stay private longer and this extends the right tail of the private firm distribution, increasing the demand for private firm capital.

4.3 Private cost of capital premium (θ)

In Figure 14, we show the effects of a change in the premium on private capital, θ . A decrease in θ increases the aggregate private capital in equilibrium. With a lower θ , the optimal abandonment threshold for private firms, $x_{D,priv}$ decreases, resulting in a longer left tail of the private firm distribution. Firms also optimally choose to stay private longer, corresponding to a higher IPO threshold \bar{x}_{IPO} . This increase in the IPO threshold has the effect of reducing the number of IPOs and public firms. However, the lower θ also incentivizes more entry by private firms, creating a greater pool of private firms that could potentially go public. The higher flow of private entrants, N , scales up the number of private firms, number of IPOs, and number of public firms. The net effect of a decline in θ on the number of public firms depends on the relative elasticities of the private entry and IPO flows with respect to the private capital illiquidity premium θ . Given our parameterization, the net effect is that a decrease in θ results in a decrease in the number of public firms and IPOs, as shown in Figure 14.

A reduction in the private capital premium θ also has the effect of increasing the average size, productivity, and profitability of both incumbent public firms and firms at the time of their IPO. However, θ has no effect on an existing public firm's decision to shut down and so in effect this increases the dispersion in the productivity of public firms.

5 Quantitative results

To quantify the effect of changes in the premium on private capital and costs of becoming and remaining public, we calibrate the model separately to match moments from the early period (1980–1998) and late period (2001–2015) of our sample. We use the model to infer the extent to which an increase in the cost being public (C_{pub}), an increase in the cost of an IPO (\mathcal{I}_{IPO}), or a decrease in the premium on private capital (θ), can explain the changes observed in the data.

In Table 2, we list the model parameters and their values under our baseline setting. We set $\alpha = 0.5$, which is consistent with the estimates of Caballero and Engel (1999), as discussed by Miao (2005). We set $\mu = 0.0048$ and $\sigma = 0.1725$ to match the mean and volatility of the growth rate of public firm earnings. We set the public discount rate to $r = 0.05$, the depreciation rate $\delta = 0.1$ and tax rate $\tau = 0.3$, consistent with values used in the investment literature. We normalize the initial productivity of private entrants, x_0 , to a value of one. The private firm fixed costs, c_f are set to a value of 0.5 to match the fraction of private firms that exit within 10 years of entry. In the version of the model where θ is an exogenous parameter, the average entry cost shock scales the total mass of firms and therefore can simply be normalized. The variance of the entry cost shock parameterizes the elasticity of entry and does influence how the entry flow N , responds to a change in model parameters. We calibrate this entry elasticity to match the elasticity of private firm entry on average Tobin’s Q in public markets.

For the remaining four parameters— $\lambda, C_{pub}, \mathcal{I}_{IPO}, \theta$ — we allow these to differ between the early and late periods of our sample. We calibrate these parameters to match four moments in the data, separately for the two periods. Table 3 presents the moments targeted in the calibration as well as the parameter values for both the early and late periods. The first moment used is the slope of the Pareto tail of public firm assets. As shown in the model, the right tail of public firms in the model follows a power law and this slope coefficient depends on μ, σ , and λ . So we set λ to match the Pareto tail coefficient in the data. The ratio of public to private firms is informative about multiple model parameters, but we use this

primarily to target the cost of being public, C_{pub} . The ratio of the IPO cost to the value at IPO is informative about the \mathcal{I}_{IPO} parameter. In the data, we measure this IPO cost as the ratio of the cost of underwriting fees and underpricing relative to the firm's market value at IPO. Finally, we use the ratio of a firm's post-IPO capital to its pre-IPO capital. This ratio is informative about θ . For a larger θ , there is a larger reduction in a firm's cost of capital once it becomes public. This lower cost of capital corresponds to a larger optimal scale post-IPO relative to pre-IPO. Since the optimal capital choice does not depend on C_{pub} or \mathcal{I}_{IPO} , the change in firm size around IPO is informative about the private capital premium θ .

Panel B of Table 3 shows the calibrated parameter values for the early and late period. The model implies a decline in λ and increases in the costs of being public (C_{pub}) and IPO (\mathcal{I}_{IPO}). Finally, the model suggests a significant decrease in the premium on private capital, going from 2% in the early period to 1.2% in the late period.

Next, we examine changes in additional model moments between the early and late periods and compare these to the changes observed in the data. In Table 4 we compare moments from the model under the calibrated parameters of the early period to those of the late period, which were not explicitly targeted in the calibration. The third column of Table 4 shows the moment change in percentage terms from the model. We see that for many of these moments, the model does a good job of matching the empirical changes, although these were not directly targeted in the calibration. As in the data, the model generates a significant reduction in the number of public firms and IPOs but an increase in the average public firm size and size at IPO. Overall, the model does relatively well in matching these observables. Given the parameter changes reported in Panel B of Table 3, this suggests that a significant reduction in private firms' cost of capital, combined with increases in the costs of being public and the IPO can replicate many of the empirical changes seen for the public firm distribution over the last two decades.

6 Alternative Explanations

Composition Shift: A contributing factor for the decline in the number of public listings could be a composition change: there might have been a drop in the type of firms for which doing an initial public offering is beneficial. For example, some of the decline in public firms could be driven by a relative increase in the types of companies that require less financing at a large scale, such as those in the technology sector. To assess these compositional effects, we examine the trends in the number of publicly listed across major industries. Appendix Figure B.3 depicts the counts of both all publicly listed firms and VC/PE-financed firms for eight SIC industry divisions. Admittedly, we find very robust secular trends in the number of public firms — a steady increase from 1980 until 1996 followed and a dramatic decline thereafter — for the majority of industry divisions, including construction manufacturing, utilities, trade, finance, and services.

We further investigate whether the downward trend in the number of public listings is also germane for the high-technology industries. Following the study by Hecker (2005), we classify an industry to be high tech if the share of jobs in that industry that are held by STEM (Science, Technology, Engineering, and Mathematics) workers is at least twice as high as the average level for all industries. More details are provided in Appendix A.3. We document that both in high-technology and non high-technology industries the number of publicly listed has declined by more than 50% from 1996 until 2018 (see Appendix Figure B.4). This evidence suggest sthat the decline in the number of public firms is a widespread phenomenon and can not be attributed to a decline in the type of firms for which conducting an IPO is beneficial.

M&A Activity. Another potential driver behind the decline in the firm’s propensity to go public is that in the recent years private firms have been entering the public markets by being acquired by publicly traded firms rather than by conducting an IPO themselves. To this end, we investigate the trends in the number of acquisitions with a public acquirer and non-public target using the SDC M&A database. Appendix A.2 provides more details on how we identify whether an acquirer/target is a public or non-public firm. We find

that the number of private firms entering the public markets through an acquisition has dropped significantly starting from 1998, as shown Panel A of Appendix Figure B.6. This secular trend is robust to whether we consider deals which resulted in 100% ownership for an acquirer or deals with both U.S. public and non-public targets. Moreover, we continue to find a similar decline in the number of M&A deals when we restrict our attention to public acquirers which have been PE/VE-financed (see Panel B of Appendix Figure B.6). These findings lead us to conclude that the changes in the M&A activity are unlikely to drive the decline in the number of U.S. public listings.

We further investigate the exit rates across different cohorts of VC/PE-financed private firms classified by the year of their first round of financing. The exit state is measured ten years after the first financing round, i.e. if a firm received its first funding in 1996 we measure its exit as of 2006. We consider three exit types of interest: going public, being acquired by a public firm, and being acquired by a private firm. As shown in Appendix Figure B.7, the private firms' propensity to enter the public markets through an acquisition is quantitatively similar for 1996 and 2007 cohorts, while the private firms' propensity to IPO has steadily declined over time. Moreover, the combined entry rates of the private firms into the public market – through an IPO and an acquisition by a public firm – has declined from about 30% in 1996 to 17% in 2007, further suggesting the decline in the number of public firms in the U.S. cannot be explained by the increased M&A activity.

7 Conclusion

Since 1996, the number of publicly listed firms in the US has declined by 50%. There are currently as many publicly listed firms as there were 40 years ago. We collect a set of facts on the change in the distribution of public and private firms that relate to this decline in public listing. We then develop a model of a firm's choice to become public and use the model to evaluate the extent to which two prominent explanations — an increase in the costs of operating as a public company or a decrease in the cost of capital for private firms — can explain these changes observed over the last two decades.

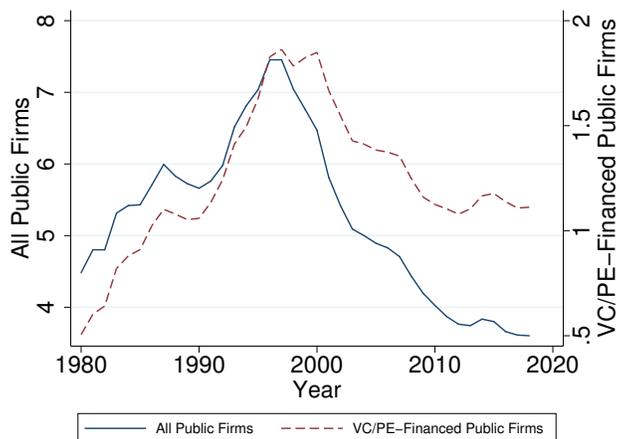
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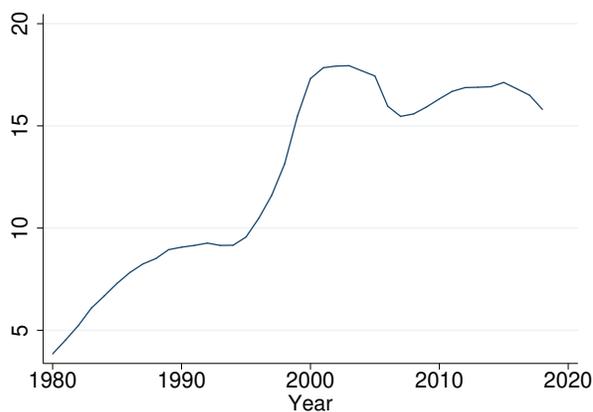
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Panel A: Number of Public Firms



Panel B: Number of Private Firms



Panel C: Propensity to Go Public

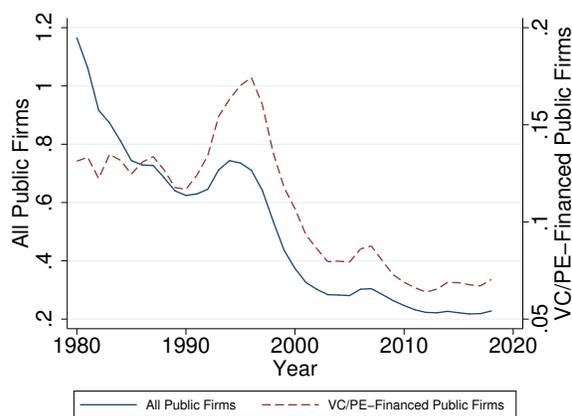
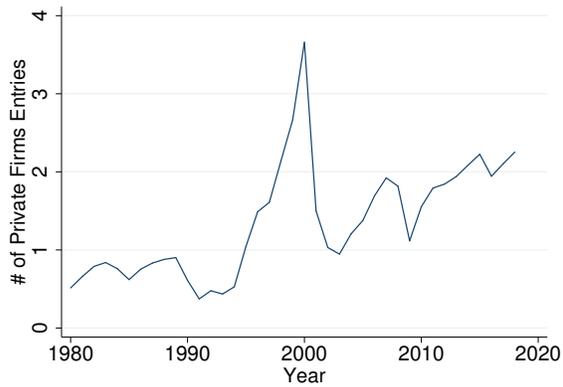


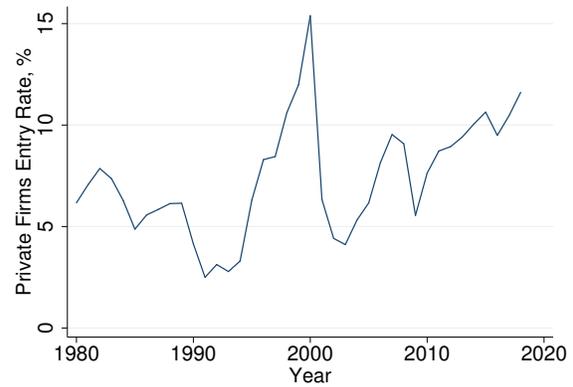
Fig. 1. Publicly Listed and Private Firms

Panel A shows the count of all publicly listed U.S. firms (solid blue line) and VC/PE-financed publicly listed firms (dashed red line). Panel B displays the number of VC/PE-financed private firms in the U.S. Panel C shows the ratio of the number of all publicly listed firms to the number of VC/PE-financed private firms (solid blue line) and the ratio of the number of VC/PE-financed publicly listed firms to the number of VC/PE-financed private firms (dashed red line). The data are annual observations from 1980 to 2018. The firm counts are expressed in thousands. The ratios are expressed in percentages.

Panel A: Number of Private Firms Entries



Panel B: Entry Rate of Private Firms



Panel C: Amount of Capital Raised

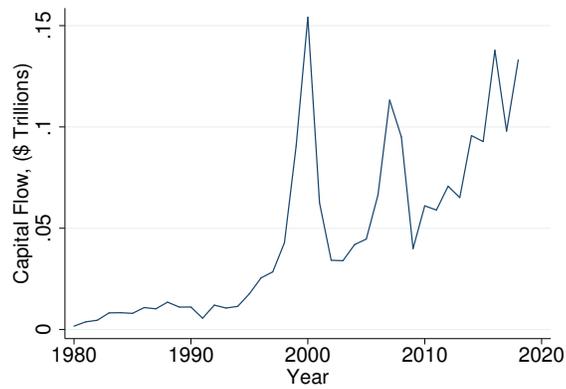


Fig. 2. Entry of Private Firms

Panel A shows the number of private firms receiving their first round of financing from VC/PE funds in each year. The firm counts are expressed in thousands. Panel B shows the the number of private firms receiving their first round of financing from VC/PE funds scaled by the number of VC/PE-financed private firms and all publicly listed firms in each year. The entry rate is expressed in percentages. Panel C shows the aggregate amount of capital received by private firms from VC/PE funds in each year. The data are annual observations from 1980 to 2018, and are expressed in trillions of dollars.

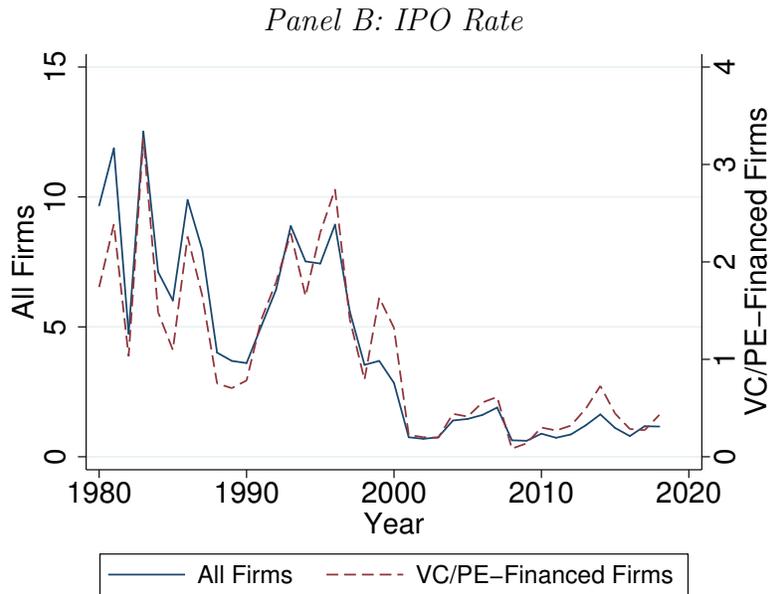
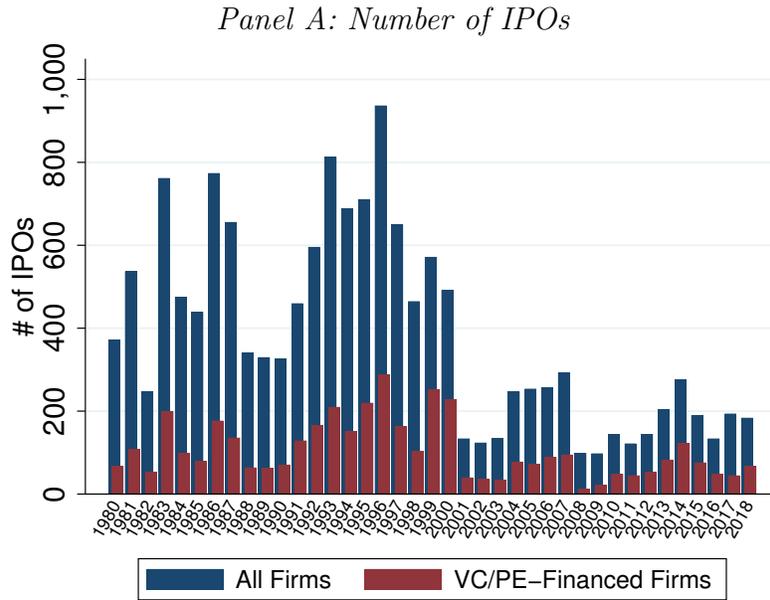


Fig. 3. Entry Rate of Public Firms

The Panel A shows the number of all IPOs (blue bars) and the number of IPOs among VC/PE-financed firms (red bars). Panel B shows the IPO rate, which is calculated as the ratio of the number of IPOs to the number of VC/PE financed private firms. The data are annual observations from 1980 to 2018. The IPO rates are expressed in percentages.

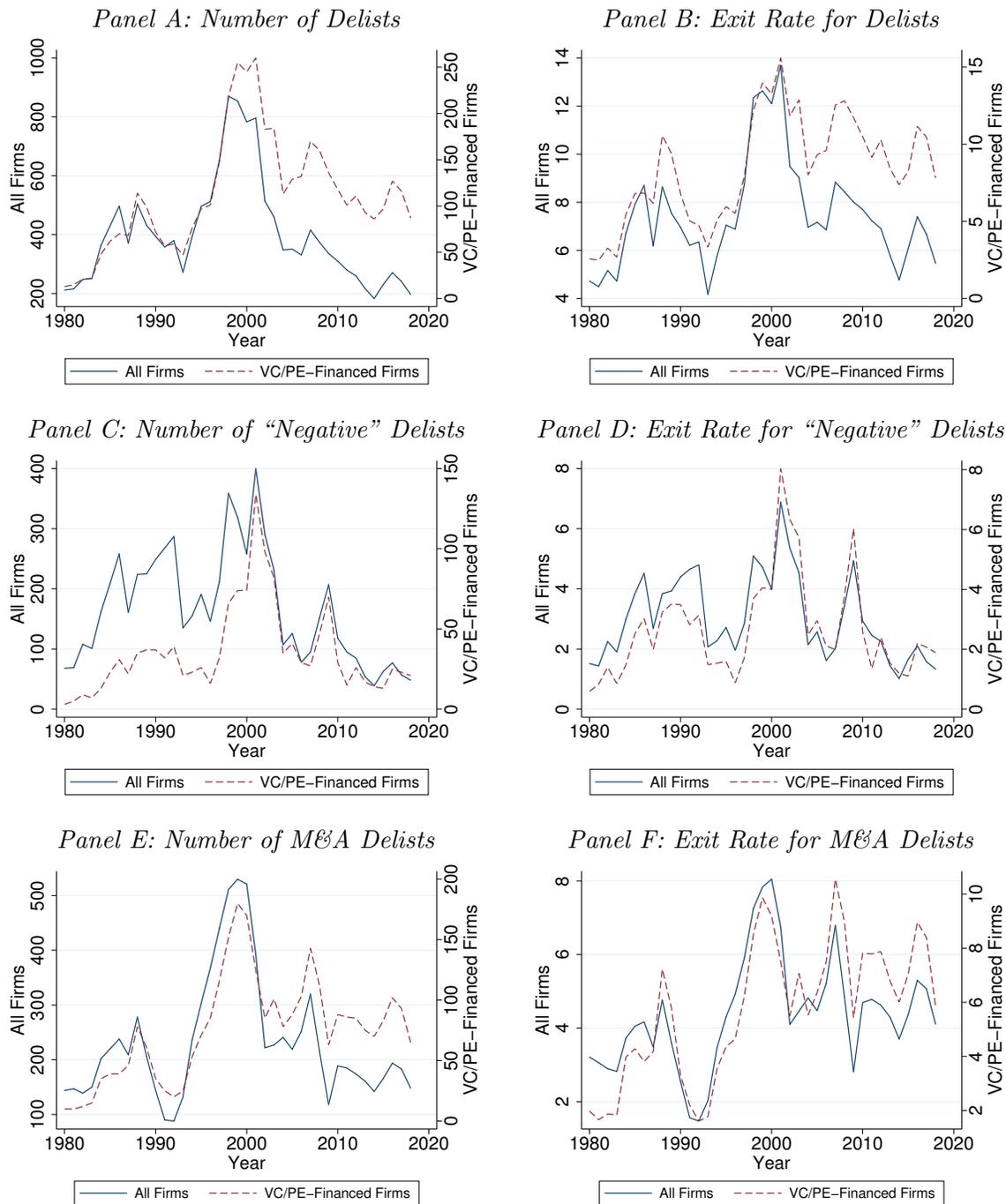


Fig. 4. Exit Rate of Public Firms

Panels A, C, and E show the number of exits among all public firms (solid blue line) and among VC/PE - financed public firms (red dashed line). Panels B, D, and F show the exit rate, defined as the ratio of firms exits to the number of publicly traded firms. Panels C and D include only exits for “negative” reasons, defined as securities with delisting codes $4xx$ and $5xx$ (excluding 573). Panels E and F include only exits through mergers and acquisitions are defined as securities with delisting codes $2xx$ and $3xx$. The data are annual observations from 1980 to 2018. The exit rates are expressed in percentages.

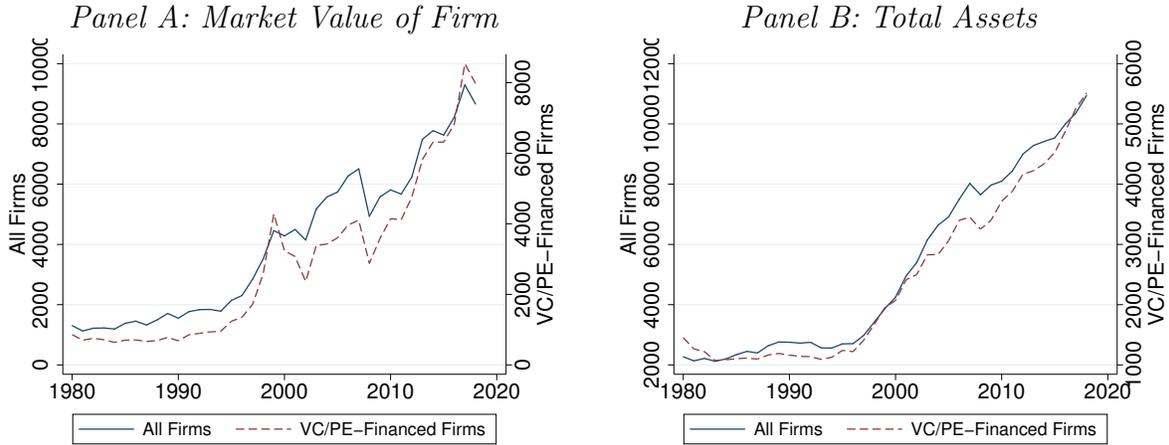


Fig. 5. Average Size of Public Firms

Figure plots the cross-sectional mean size of all publicly listed U.S. firms (solid blue line) and of VC/PE-financed firms (dashed red line). In Panel A, the firm's size is measured with market value of firm, which is defined as the sum of market value of equity and book value of debt. In Panel B, the firm's size is measured with total assets. The data are real annual observations from 1980 to 2018, and are expressed in millions of December 2009 dollars.

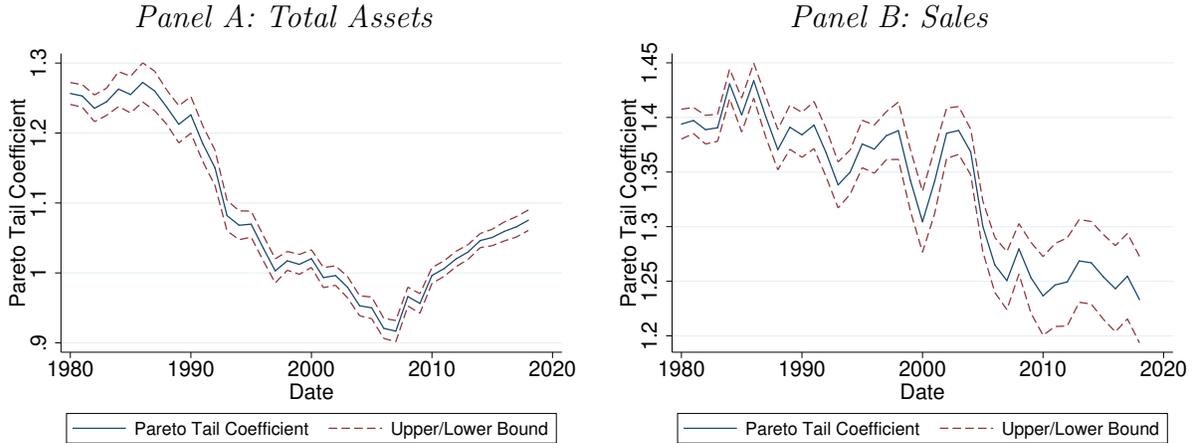


Fig. 6. Power Law Coefficient of Public Firm Size

Figure plots the power law exponent given by $Pr(size > X) = kX^{-\gamma}$ along with the 5% and 95% confidence intervals over time. The firm's size is measured with total assets (Panel A) and total revenues (Panel B). γ is estimated by running the following cross-sectional regression

$$\log(rank_{i,t}) = \alpha_t + \beta_t \log(size_{i,t}) + \varepsilon_{i,t}$$

for each year t using the top n largest firms, where n is defined by the 95th percentile of firm size in the year.

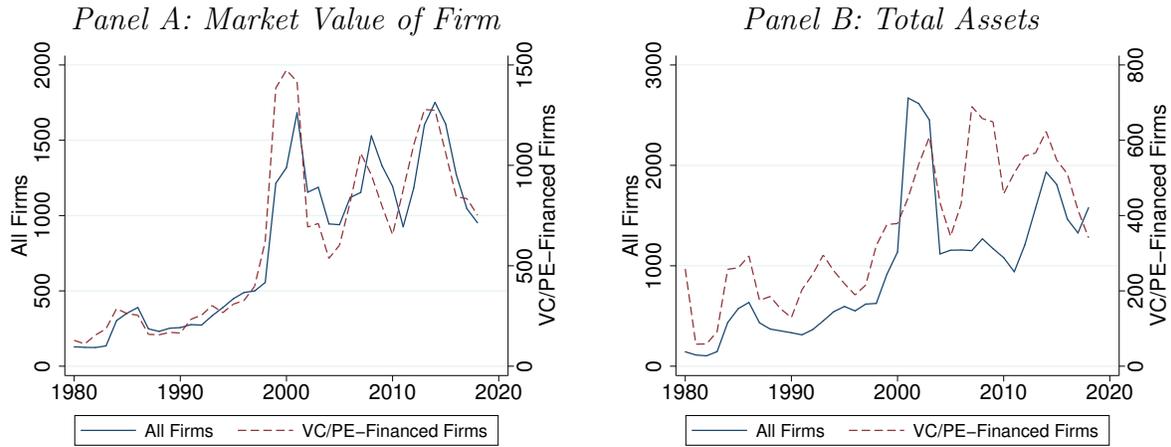


Fig. 7. Average Size of Firms at IPO

The Figure plots the cross-sectional mean size of all firms at IPO (solid blue line) and of VC/PE-financed firms at IPO (dashed red line). The means are smoothed using the three-year moving average. In Panel A, the firm's size is measured with market value of firm, which is defined as the sum of market value of equity and book value of debt. In Panel B, the firm's size is measured with total assets. The data are real annual observations from 1980 to 2018, and are expressed in millions of December 2009 dollars.

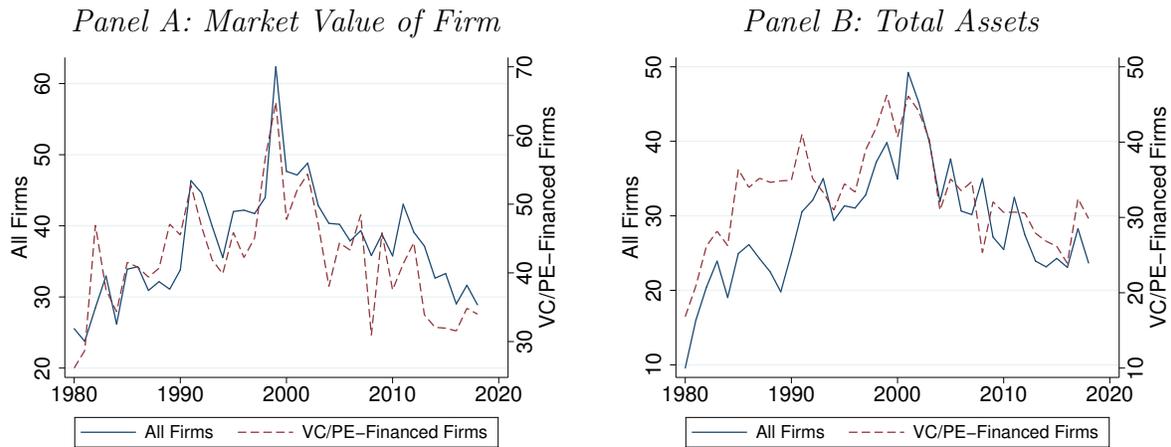


Fig. 8. Share of Public Firms Below Median Firm Size at IPO

The Figure plots the share of public firms below the median firm's size at IPO. In Panel A, the firm's size is measured with market value of firm. In Panel B, the firm's size is measured with total assets. The data are annual observations from 1980 to 2018, and are expressed in percentages.

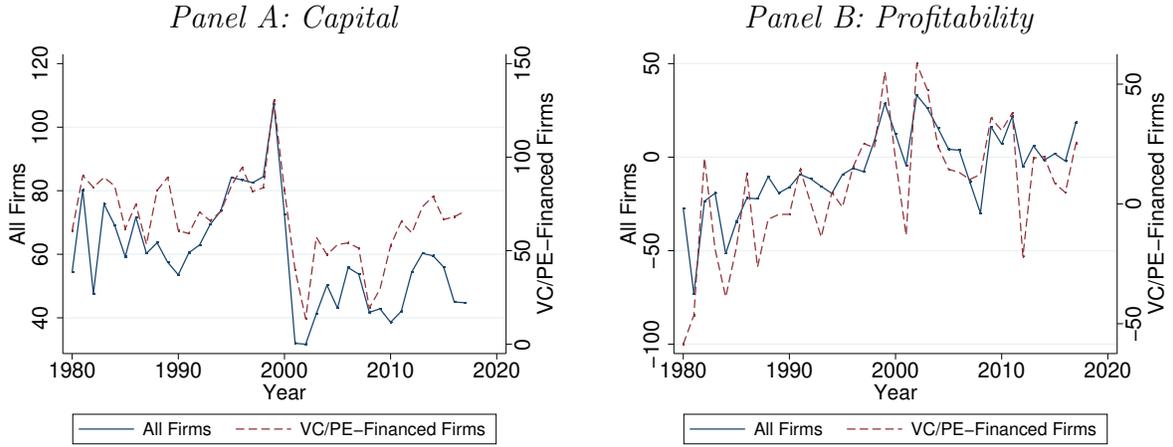


Fig. 9. Changes in Firms' Capital and Profitability around IPO

The Figure plots the cross-sectional average growth rates in firms' capital and profitability over one year before an IPO and one year after an IPO. The growth rates are calculated as

$$\Delta x_{j,t} = \frac{x_{j,t+1} - x_{j,t-1}}{0.5(|x_{j,t+1}| + |x_{j,t-1}|)},$$

where t is the year of an IPO. Panel A show changes in firms' capital, measured with net property, plant, and equipment. Panel A show changes in firms' profitability, calculated as the ratio of operating income before depreciation and total assets. The data are annual observations from 1980 to 2018, and are expressed in percentages.

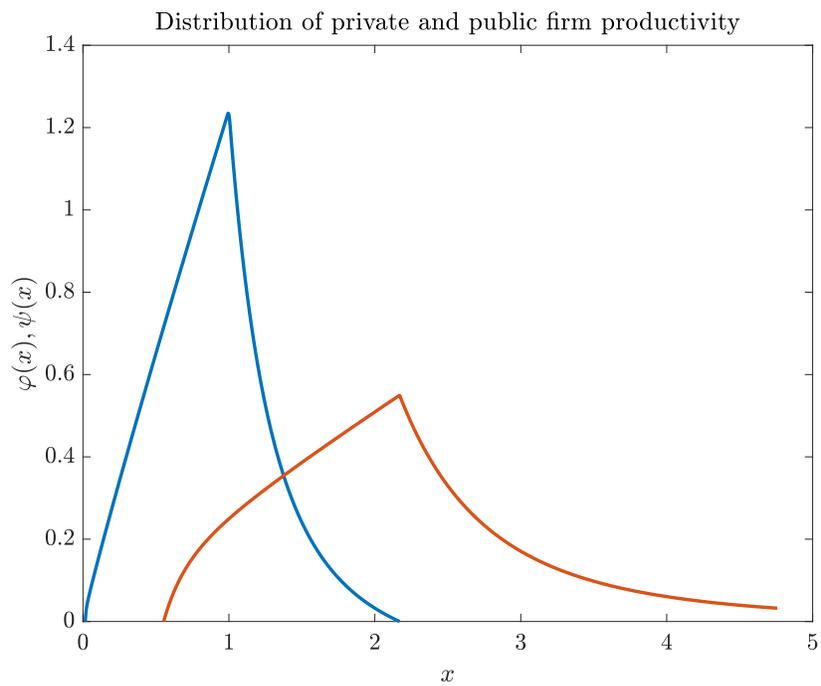


Fig. 10. **Distributions of firm productivity.** The figure displays the stationary distributions of private (blue) and public (red) firm productivity.

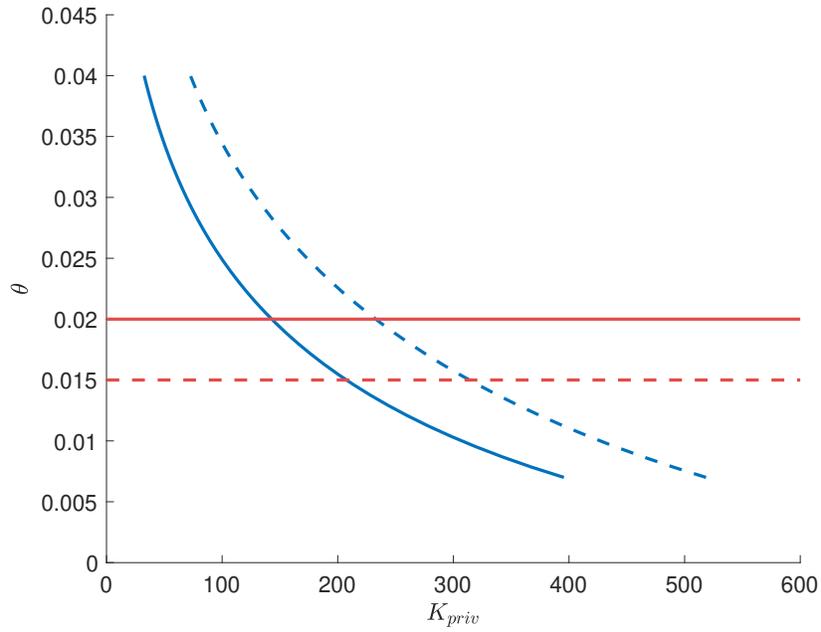


Fig. 11. **Supply and demand for private capital.** The figure shows the supply (blue) and demand (red) curves for private capital for different cases. The solid lines show the supply and demand for a benchmark parameter case. The dashed red line is the outward shift in demand for either an increase in \mathcal{C}_{pub} or \mathcal{I}_{IPO} . The dashed blue line shows a reduction in the private capital premium θ .

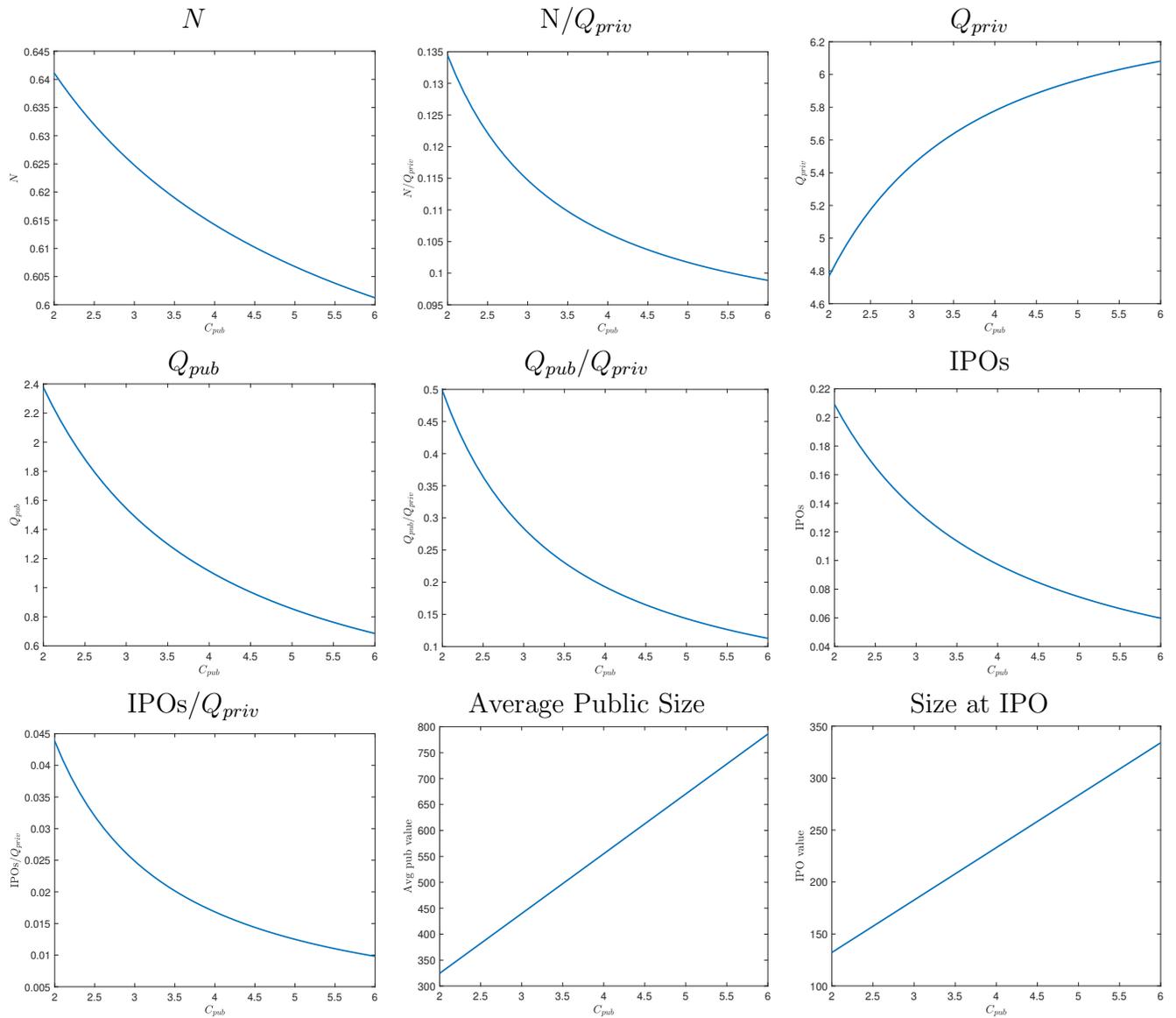


Fig. 12. **Comparative statics for C_{pub} .** The figure plots model statistics as a function of the cost of being public, C_{pub} . Q_{priv} and Q_{pub} are the masses of private and public firms. N is the flow of new private entrants and IPOs refers to the flow of firms going public.

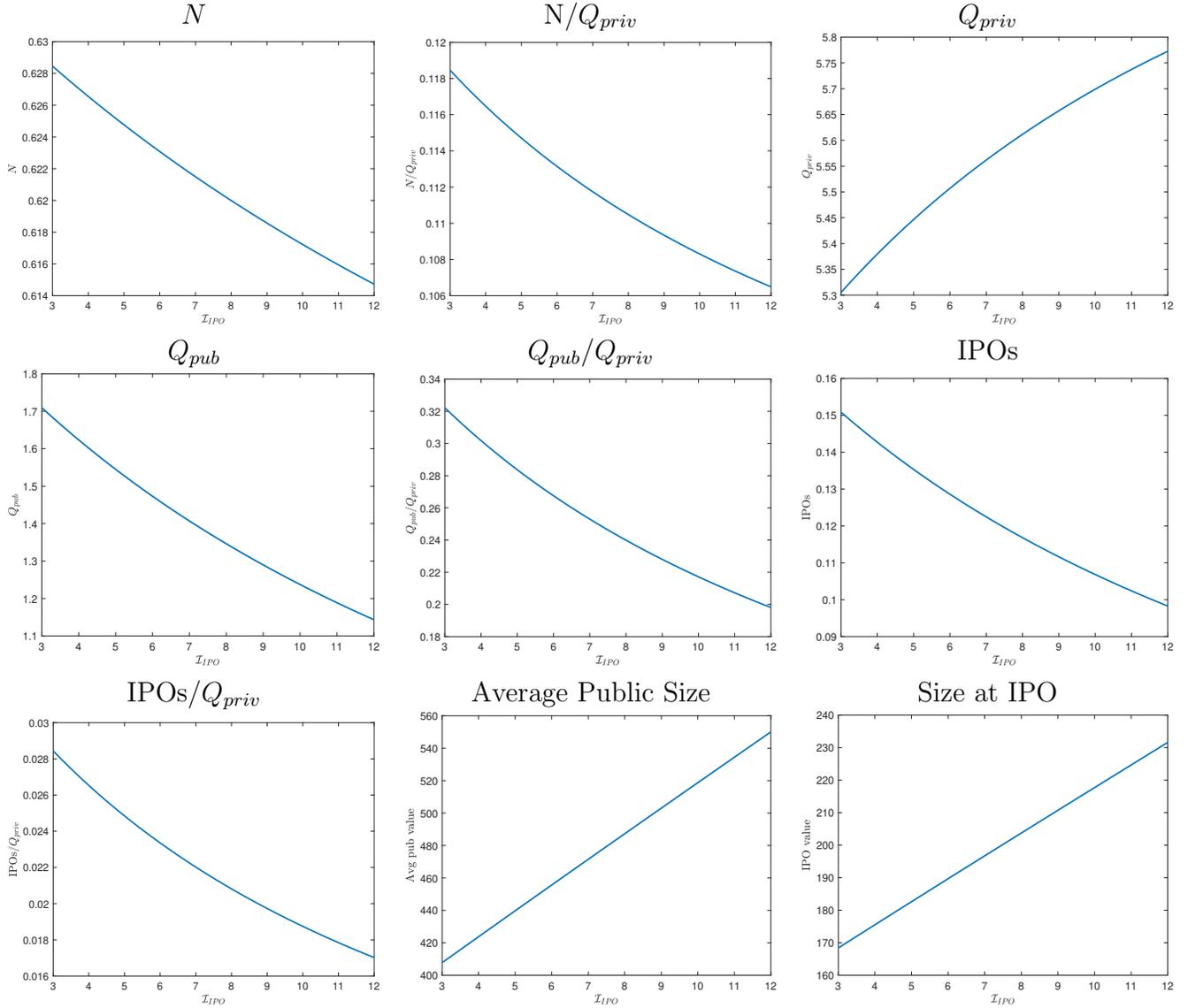


Fig. 13. **Comparative statics for \mathcal{I}_{IPO} .** The figure plots model statistics as a function of the IPO cost, \mathcal{I}_{IPO} . Q_{priv} and Q_{pub} are the masses of private and public firms. N is the flow of new private entrants and **IPOs** refers to the flow of firms going public.

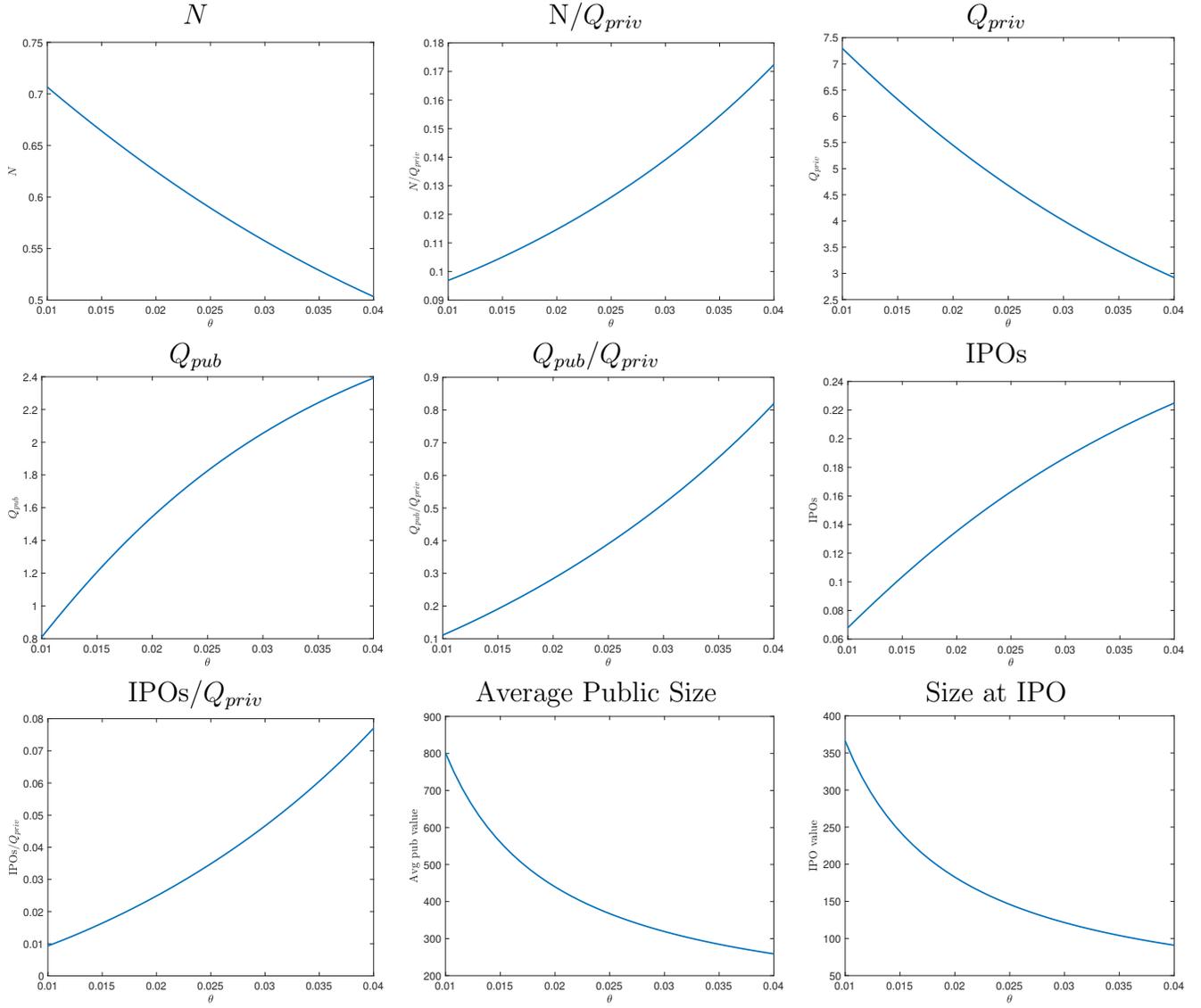


Fig. 14. **Comparative statics for θ .** The figure plots model statistics as a function of the premium on private capital, θ . Q_{priv} and Q_{pub} are the masses of private and public firms. N is the flow of new private entrants and IPOs refers to the flow of firms going public.

Table 1: Empirical Facts: Early vs. Late Period

	All Firms			VC/PE-Financed Firms		
	Early	Late	% Change	Early	Late	% Change
Firms' counts						
Number of public firms [†]	7.16	3.80	-46.89	1.72	1.13	-34.52
Number of private firms [†]	10.79	16.90	56.57	10.79	16.90	56.57
Propensity to go public, % [†]	67.36	22.51	-66.59	16.08	6.66	-58.56
Entry & exit of public firms						
Number of IPOs	0.56	0.18	-67.41	0.13	0.06	-54.80
IPO rate, %	7.08	1.08	-84.71	1.66	0.36	-78.24
Number of exits	0.41	0.36	-12.77	0.07	0.14	86.62
Negative delists	0.19	0.15	-23.35	0.03	0.05	81.56
M&A delists	0.22	0.21	-3.78	0.05	0.09	89.25
Exit rate, %	6.81	7.80	14.59	5.94	10.55	77.63
Negative delists	3.16	3.08	-2.54	2.11	3.37	59.75
M&A delists	3.64	4.72	29.46	3.83	7.18	87.48
Size of public firms						
Log(Total assets) [†]	5.31	6.60	24.12***	5.01	6.14	22.38***
	(2.11)	(2.15)		(1.89)	(2.06)	
Log(Market value of firm) [†]	5.40	6.63	22.87***	5.43	6.55	20.67***
	(2.03)	(2.10)		(1.80)	(1.97)	
Size of public firms at IPO						
Log(Total assets)	3.91	5.43	38.87***	4.03	5.02	24.52***
	(1.78)	(1.74)		(1.42)	(1.37)	
Log(Market value of firm)	4.40	5.83	32.46***	4.78	5.87	22.69***
	(1.51)	(1.50)		(1.31)	(1.29)	
Power law coefficient of public firms size						
Total assets	1.18	1.02	-13.45***	1.31	1.20	-8.66***
Revenues	1.44	1.33	-7.45***	1.59	1.29	-18.63***
Changes in firms' characteristics around IPO						
Capital	72.34	48.96	-23.38***	77.59	57.50	-20.09***
	(69.58)	(67.18)		(66.65)	(67.68)	
Profitability	-16.30	4.73	21.03***	0.07	17.95	17.87***
	(108.94)	(95.68)		(112.09)	(106.12)	

The table reports the changes in firms' counts, entry and exit rates, size, and power law coefficient between the early and late periods. The table shows the changes both for all public firms and VC/PE-financed public firms. The early-period averages and standard deviations are calculated over the period from 1980 to 1998 (from 1994 to 1998 for moments marked with †). The late-period moments are calculated over the period from 2001 to 2015 (from 2011 to 2015 for moments marked with †). Standard deviations are reported in the parentheses. The firms' counts are expressed in thousands. The data on total assets, market value of firm, and revenues are real annual observations, and are expressed in millions of December 2009 dollars. The changes between the early and late periods, as well as rates, are expressed in percentages. For the changes in the cross-sectional moments, ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 2: Model Parameters

Parameter	Definition	Value
μ	Productivity drift	0.0048
σ	Productivity volatility	0.1725
α	Curvature of profit function	0.5
c_f	Fixed operating cost	0.5
r	Public firm discount rate	0.05
τ	Corporate tax rate	0.30
δ	Capital depreciation rate	0.1
x_0	Initial productivity of private entrant	1
$\log(\bar{c}_e)$	Mean entry cost	4
σ_{ce}	Volatility of entry cost	1.2

The table reports the parameter values used in the baseline specification of the model. Values are annualized where applicable.

Table 3: Model moments and parameters, early and late periods

<i>Panel A: Targeted moments</i>				
	Early		Late	
	Model	Data	Model	Data
Pareto tail, public assets	1.305	1.307	1.22	1.20
# Public / # Private	0.161	0.161	0.066	0.066
IPO cost / IPO value	0.020	0.020	0.0193	0.023
Post-/Pre- IPO capital	1.918	1.926	1.70	1.678

<i>Panel B: Parameters</i>			
	Early	Late	Change (%)
λ	0.075	0.064	-14.7
C_{pub}	0.74	0.96	30.6
\mathcal{I}_{IPO}	0.9	2.3	155.5
θ	0.020	0.012	-41.6

Panel A reports the moments targeted in the calibration, both data and model, for the early period (1980–1998) and late period (2001–2015). Panel B shows the calibrated parameter values for the early and late periods. See Table 2 for the other parameter values.

Table 4: Moment changes, model and data

	Model Early	Model Late	Model Change, %
# Public firms	0.953	0.603	-36.7
# Public/#Private	0.158	0.067	-57.8
IPOs	0.079	0.041	-47.8
IPOs/ # Private firms	0.013	0.005	-65.2
Average capital , public	89.0	230.1	158.6
Average firm value, public	116.3	358.8	208.5
Capital at IPO	38.5	82.8	115.4
Firm value at IPO	44.4	119.5	169.0
Median age at IPO	8.9	14.6	64.8
Capital growth around IPO(%)	91.8	70.7	-23.0
Private entrants	0.569	0.667	17.3
# Private firms	6.034	9.054	50.0
Private entry rate	0.094	0.074	-21.8

The table compares moments for the early (1980–1998) and late (2001–2015) periods. The first two columns report moments computed from the model, for the parameters listed in Tables 2 and 3. The third column gives the percentage change of the model moment from the early to late period value.

Table 5: Effects of individual parameter changes

	All changed	Only θ	Only C_{pub}	Only \mathcal{I}_{IPO}	Only λ
# Public firms	-36.7	-37.7	-25.7	-28.5	58.0
# Public/#Private	-57.8	-47.3	-28.0	-31.1	30.1
IPOs	-47.8	-40.1	-26.0	-30.3	38.4
IPOs/ # Private firms	-65.2	-49.3	-28.2	-32.8	13.9
Average capital , public	158.6	52.7	24.5	27.8	16.3
Average firm value, public	208.5	56.5	24.8	29.8	35.3
Capital at IPO	115.4	57.9	24.9	30.6	-8.0
Firm value at IPO	169.0	70.3	26.3	32.4	5.2
Median age at IPO	64.8	33.8	16.9	19.7	0.0
Post-/pre-IPO capital	-11.0	-10.1	0.7	0.8	0.2
Private entrants	17.3	8.8	-1.1	-1.3	10.1
# Private firms	50.0	18.3	3.1	3.7	21.5
Private entry rate	-21.8	-8.1	-4.1	-4.8	-9.3

The table shows the percent change for changes in different parameters of the model. The first column shows the changes when all four parameters — $\lambda, \theta, C_{pub}, \mathcal{I}_{IPO}$ — are changed from their early to late period values. In each of the following columns, we change a single parameter from its early to late period value, holding all other parameters fixed at their early period calibrated values. The values reported are the percentage point change in the statistic in the model.

A Data Appendix

A.1 Identifying VC/PE-financed Firms in the CRSP/Compustat Dataset

We merge the VenturExpert dataset to the CRSP/Compustat Merged dataset in order to identify which VC/PE-financed firms exited private markets via an IPO and when. This merge also allows us to split the universe of the CRSP/Compustat firms into two groups – firms that were at some point of their life cycle VC/PE-backed and firms that did not receive any funding from venture capital and private equity funds.

We start with the VenturExpert database which allows us to identify a set of the U.S. companies that received VC/PE financing.⁹ All firms that raised at least one round of financing, except for leveraged buyout financing, between 1980 and 2018 are included. The sample consists of 52,941 unique portfolio companies. Among these 52,941 companies, 5,101 have potentially exited private markets via an IPO. We identify these candidates for public firms in the following way. First, the VenturExpert collects data on firms’ exit events: IPOs, buybacks, secondary and trade sales, reverse takeovers, and write offs. Such exit information is available for 14,565 firms, 3,605 of which have been recorded with an IPO exit and 3,100 have been listed on NYSE, AMEX or NASDAQ. Second, the VenturExpert provides information on a company’s current status (e.g., “Went Public” , “Active” , “Merger”) and public status (e.g., “Public”, “Private”, “Subsidiary”). We only have this information recorded as of 2019 year end. This means that a set of companies with the status “Went Public” does not necessarily capture all VC/PE-financed firms that exited private markets via an IPO. For example, a company with the status “Acquisition” as of 2019 could have gone public in 2015 and a few years thereafter got acquired by another firm. Hence, our set of potential candidates for public firms is a union of (i) 3,605 firms with exit type “IPO”, (ii) 4,357 firms with status “Went Public”, and (iii) 4,490 firms with public status “Public”. To minimize the classification error, we conduct the merge for a full universe of VC/PE-financed compa-

⁹Another database which covers venture capital deals in the U.S. is the VentureSource dataset. However, the majority of companies in the VentureSource are also in the VenturExpert. Puri and Zarutskie (2012) document that only 10% of the companies present in the two databases are exclusively in the VentureSource.

nies, but we use the information on a company’s exit type and current status provided in the VenturExpert to assess the quality of our matches.

To match the VenturExpert to the CRSP/Compustat dataset, we rely on a company’s name and full address, that is, city, state and zipcode. Overall, we identify that 4,605 companies out of 52,941 conducted an IPO and satisfy the criteria of Doidge et al. (2017) (see Section 2 for additional details). We first attempt to match on a company’s full name and full address. This step delivers 52% of all the matches (see Panel A of Table A.1). Next, we merge firms using their full name and partial address (e.g. city and state, but not zipcode). This step allows us to match another 23%. Another 14% of matches are obtained by matching only a full name. Finally, we repeat the above three steps but this time using the partial name of a company. To assess the quality of our matches, we check what fraction of our matches has been identified as a potential public firm in the VenturExpert, as well as compare the IPO year reported in the two databases for companies with exit type “IPO” (see Panel B of Table A.1). Overall, we find that around 60%-90% of the matched companies (depending on a matching criterion) have been among potential public candidates as identified in the VenturExpert. However, if we were only to rely on the IPO dates reported in the VenturExpert, we would have nontrivially underestimated the number of VC/PE-financed firms exiting private markets via an IPO.

Table A.1: Matching Results between VenturExpert and CRSP/Compustat

Panel A: Number of Matches by Matching Rounds

	# of Matched Firms (4605 firms)	% of Matched Firms
Full Name, City, Zip, State	2390	51.90
Full Name, City, State	370	8.03
Full Name, Zip, State	96	2.08
Full Name, State	590	12.81
Full Name	630	13.68
<i>Total</i>	4076	88.51
Partial Name, City, Zip, State	331	7.19
Partial Name, City, State	64	1.39
Partial Name, Zip, State	13	0.28
Partial Name, State	101	2.19
Partial Name	20	0.43
<i>Total</i>	529	11.49

Panel B: Match Quality by Matching Rounds

	# of Matched Firms (4605 firms)	% with Public Status “Public”	% with Status “Went Public”	% with Exit Type “IPO”	% with Public Flag	Average Difference in IPO Year
Full Name, City, Zip, State	2390	73.56	71.17	67.41	85.94	-0.04
Full Name, City, State	370	73.24	71.89	59.19	80.81	-0.01
Full Name, Zip, State	96	81.25	81.25	72.92	91.67	-0.77
Full Name, State	590	78.14	77.29	67.46	86.78	-0.11
Full Name	630	54.29	52.70	43.33	61.59	0.26
<i>Total</i>	4076	71.39	69.50	63.08	81.97	
Partial Name, City, Zip, State	331	68.88	66.77	61.63	79.15	0.02
Partial Name, City, State	64	65.62	64.06	56.25	75.00	-0.56
Partial Name, Zip, State	13	53.85	46.15	38.46	61.54	0.00
Partial Name, State	101	59.41	58.42	43.56	64.36	1.07
Partial Name	20	85.00	80.00	65.00	100.00	-7.77
<i>Total</i>	529	66.92	64.84	57.09	76.18	

Panel A reports the number and percent of matches between the VenturExpert and CRSP/Compustat databases by a matching round. Panel B shows the percent of companies among matches, which have either public status “Public”, or status “Went Public”, or exit type “IPO”, or any of the above by a matching round. Panel B also reports the average difference between the IPO year reported in the VenturExpert and CRPS/Compustat databases for firms with exit type “IPO”.

A.2 Matching the CRSP/Compustat Dataset with the Thomson Reuters SDC Platinum M&A Dataset

We merge the Thomson Reuters SDC Platinum Mergers and Acquisitions database to the CRSP/Compustat database in order to identify firms which (i) enter public market via an acquisition by a public firm, and (ii) exit public market via an acquisition by a private firm. To merge the two databases, we rely on the securities' identifier – the CUSIP number.

Admittedly, we underestimate the number of conducted M&A deals, since SDC M&A dataset typically covers larger acquisitions and acquisitions by public acquirers. However, comparing the number of M&A deals covered in the SDC database with the number of deals reported by the Institute for Mergers, Acquisitions and Alliances (IMMA) suggests that underreporting is relatively small. The SDC database provides information for over 85% of merger and acquisition deals in each year over our sample period (see Appendix Figure B.5). Note that we focus only on the U.S. M&A deals, i.e. deals in which either an acquirer or a target is a U.S. firm as identified by *anation* and *tnation*, respectively.

Identifying Non-Public Firms Acquired by Public Firms in the SDC Platinum M&A Dataset. To identify deals in which the acquirer is a public firm, we merge the set of firms in the CRSP/Compustat dataset to firms listed as an acquirer in the deals from the SDC database using the acquirer's CUSIP number (*acusip*). An acquirer is classified as a public firm if its CUSIP number is matched to the CRSP securities' numbers. Importantly, we also require that it satisfies the criteria of Doidge et al. (2017). Similarly, we identify deals in which the target is a public firm. But rather than matching firms in the CRSP/Compustat dataset to firms in the SDC database listed as an acquirer, we match them to firms listed as a target using the target's CUSIP number (*master_cusip*).

Note that this definition of a public firm implies that non-public firms include foreign firms (either privately held or publicly listed), U.S. privately held firms, and U.S. publicly listed firms that do not meet the criteria of Doidge et al. (2017) (e.g., publicly listed firms that have never been listed NYSE, AMEX, or NASDAQ stock exchanges).

Identifying Public Firms Acquired by Non-Public Firms in the CRSP/Compustat

Dataset. These firms are a subset of the CRSP/Compustat firms satisfying the Doidge et al. (2017) criteria and exiting through mergers and acquisitions. We therefore restrict our sample to securities with delisting codes *2xx* and *3xx*. Then, we match this set to firms to firms listed as targets in the acquisition deals from the SDC database using the target’s CUSIP number (*master_cusip*). We only keep deals which have been completed and become effective in a two year window from the CRSP delisting year and which have resulted in more than 50% ownership for an acquirer. These restriction are on the conservative side, allowing us to avoid underreporting of acquisitions. Alternatively, we could have required the effective year of an acquisition being the same as the CRSP delisting year, as well as 100% ownership for an acquirer.

A.3 Identifying High-Technology Industries

To identify high-technology industries, we follow the study by Hecker (2005) which relies on the Bureau of Labor Statistics (BLS) definition of high-technology industries — those that have high concentrations of workers in STEM (Science, Technology, Engineering, and Mathematics) occupations. More specifically, an industry is considered to be high tech if the share of jobs in that industry that are held by STEM workers is at least twice as high as the average level for all industries. Technology-oriented occupations include the following occupational groups: computer and mathematical scientists (SOC code 15–0000); engineers (SOC code 17–2000); drafters, engineering, and mapping technicians (SOC code 17–3000); life scientists (SOC code 19–1000); physical scientists (SOC code 19–2000); life, physical, and social science technicians (SOC code 19–4000); computer and information systems managers, (SOC code 11–3020); engineering managers (SOC code 11–9040); and natural sciences managers (SOC code 11–9120). To calculate industries’ shares of STEM employment, Hecker (2005) relies on the 2002 National Employment Matrix from the BLS which reports occupational employment by NAICS industry groups. As of 2002, a typical four digit NAICS industry had 4.9% of employment in high-technology oriented occupations. Therefore, only industries with the share of STEM employment above 9.8% were classified as

high tech. These high-technology industries were further classified into three groups: Level I consists of industries with the share of STEM workers at least 5 times above the average level for all industries, Level II — at least 3 but less than 5 times above the average level, Level III — at least 2 but less than 3 times above the average level. The full list of high-technology industries, along with the shares of employment in technology-oriented occupations as of 2002, is reported in Table 4 of Hecker (2005). For our analysis, we classify a firm to be part of a high-technology industry if its NAICS code from the S&P Compustat (*naics*) is among the NAICS codes of high-technology industries as identified by Hecker (2005).

B Additional Figures and Tables

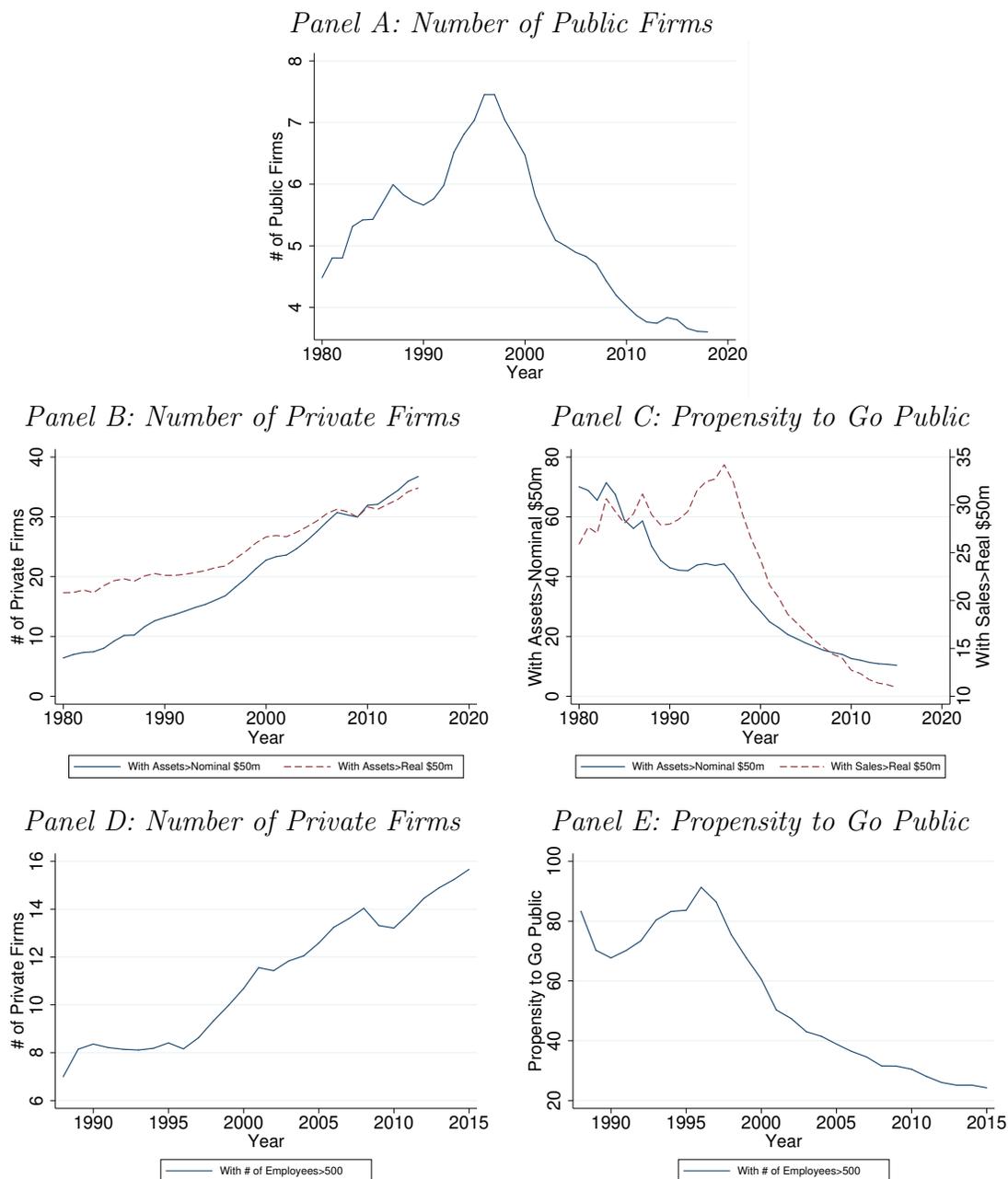
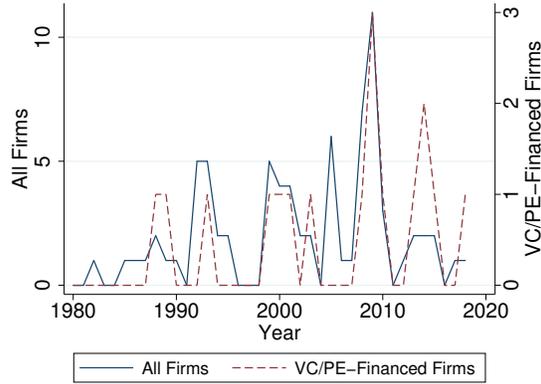


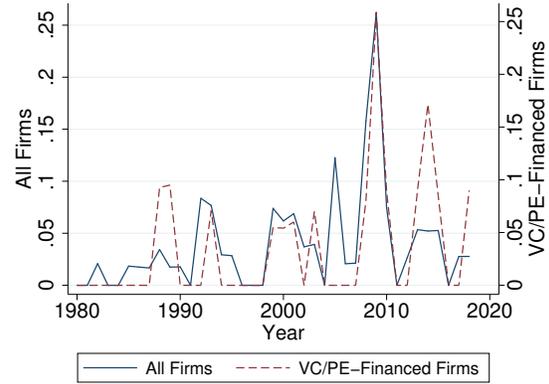
Fig. B.1. Publicly Listed and Private Firms

Panel A shows the count of publicly listed U.S. firms. Panel B and D display the number of U.S. private firms with assets above \$50m and with more than 500 employees, respectively. Panel C and E shows the ratio of the number of publicly listed firms to the number of private firms with assets above \$50m and with more than 500 employees, respectively. The firm counts are expressed in thousands, and the ratios are expressed in percentages.

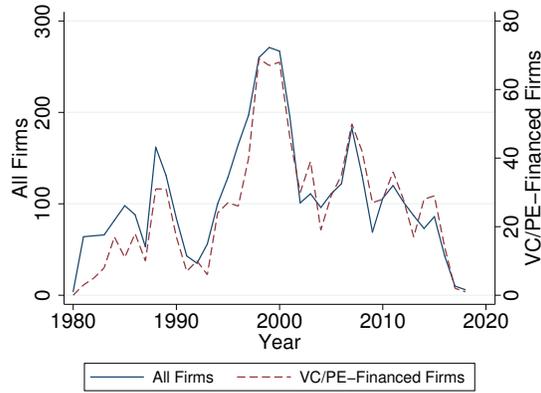
Panel A: Number of Gone Private Delists



Panel B: Exit Rate for Gone Private Delists



Panel C: Number of M&A Delists



Panel D: Exit Rate for M&A Delists

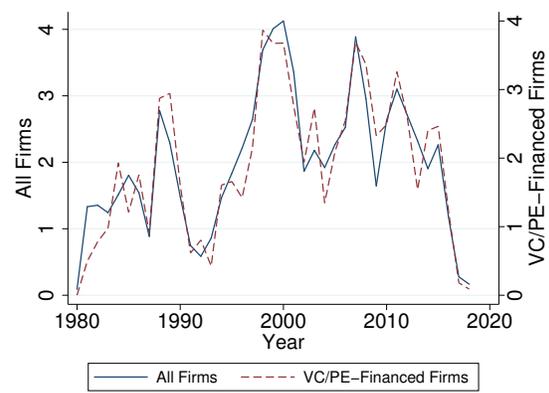
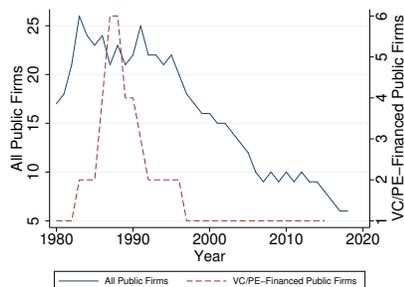


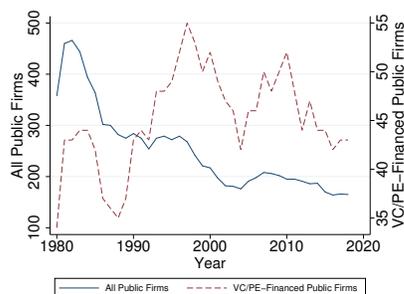
Fig. B.2. Exit Rate of Public Firms

Panels A and C show the number of exits among all public firms (solid blue line) and among VC/PE -financed public firms (red dashed line). Panels B and D show the exit rate, defined as the ratio of firms exits to the number of publicly traded firms. Panels A and B include only exits with a reason “gone private”, defined as securities with the delisting code 573. Panels C and D include only exits through mergers and acquisitions by a non-public acquirer are defined as securities with delisting codes 2xx and 3xx. More details are provided in Appendix A.2. The data are annual observations from 1980 to 2018. The exit rates are expressed in percentages.

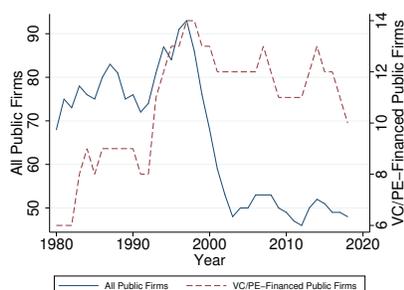
Panel A: Agriculture, Forestry & Fishing



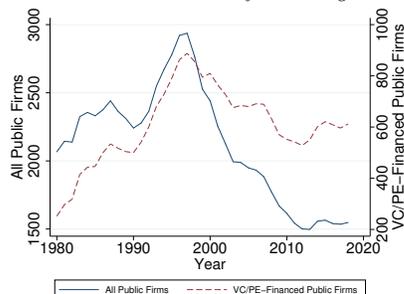
Panel B: Mining



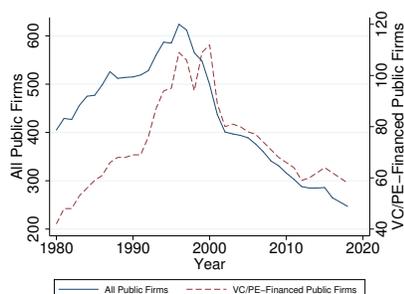
Panel C: Construction



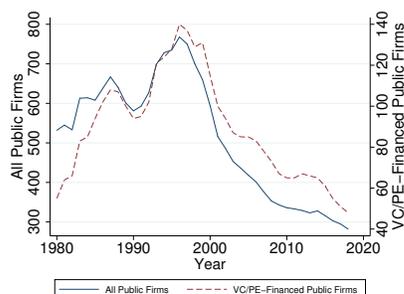
Panel D: Manufacturing



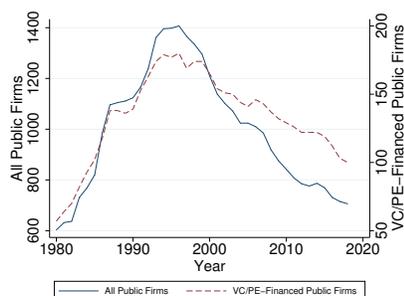
Panel E: Utilities



Panel F: Trade



Panel G: Finance



Panel H: Services

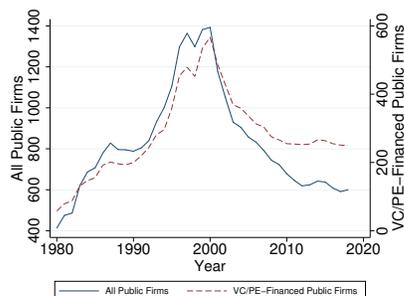


Fig. B.3. Number of Public Firms - Industry Decomposition

Figure shows the count of all publicly listed U.S. firms (solid blue line) and VC/PE-financed publicly listed firms (dashed red line) across different industries: (a) agriculture, forestry and fishing (SIC codes 100-999), (b) mining (SIC codes 1000-1499) (c) construction (SIC codes 1500-1799), (d) manufacturing (SIC codes 2000-3999), (e) transportation, communications, electric, gas and sanitary service (SIC codes 4000-4999), (f) wholesale and retail trade (SIC codes 5000-5999), (g) finance, insurance and real estate (SIC codes 6000-6799), and (h) services (SIC codes 7000-8999). The data are annual observations from 1980 to 2018.

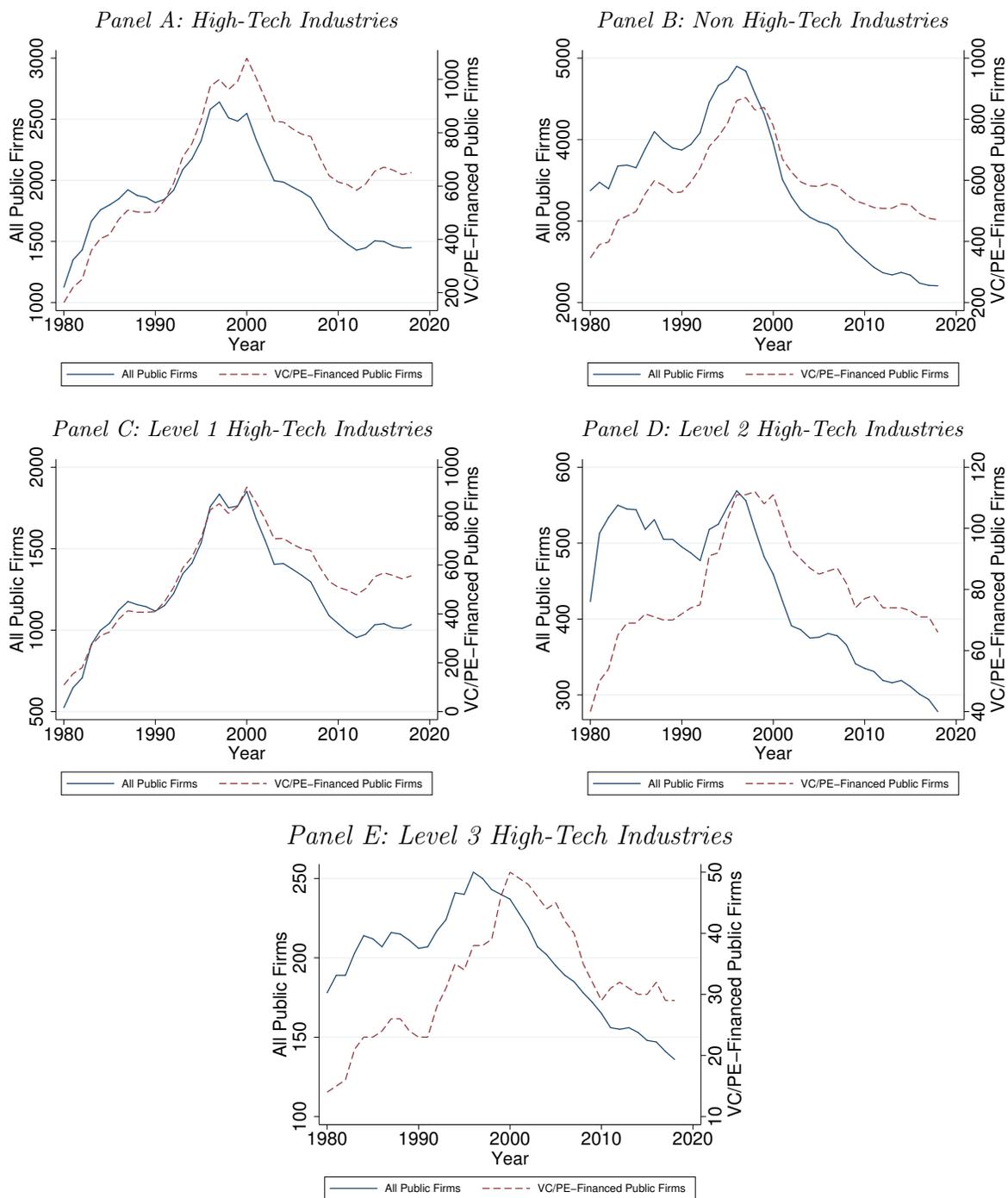


Fig. B.4. Number of Public Firms - High-Technology Industries

Figure shows the count of all publicly listed U.S. firms (solid blue line) and VC/PE-financed publicly listed firms (dashed red line) across high-technology and non high-technology industries. An industry is considered to be high tech if the share of jobs in that industry that are held by STEM workers is at least twice as high as the average level for all industries as of 2002. More details are provided in Appendix A.3. The data are annual observations from 1980 to 2018.

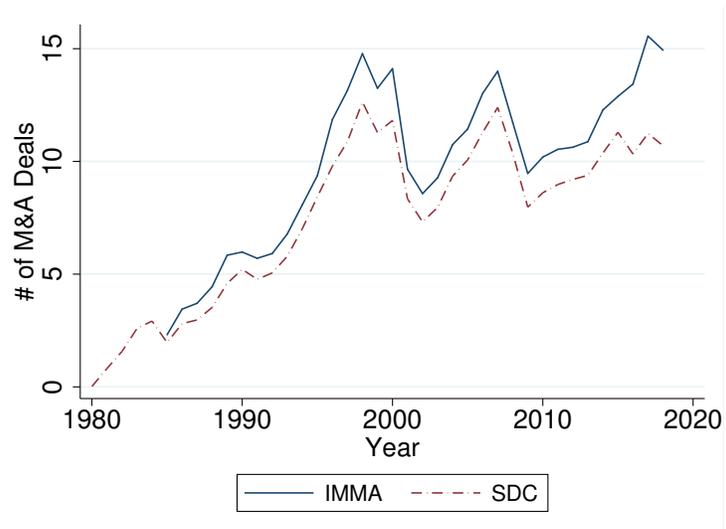
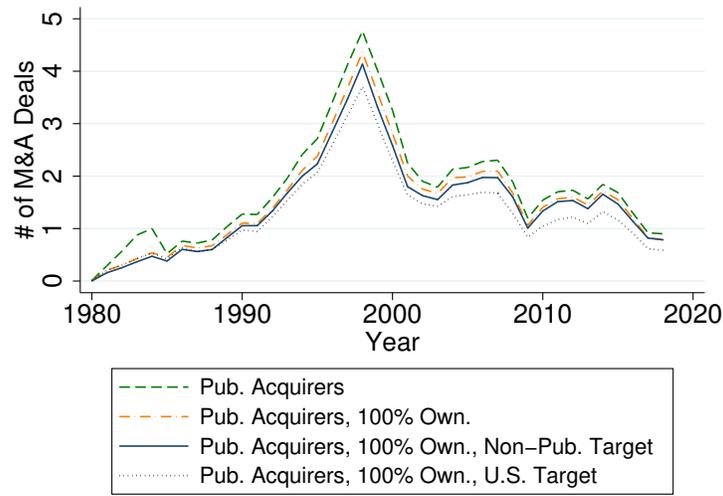


Fig. B.5. Number of M&A Deals

Figure shows the number of M&A deals in the U.S. as reported by the Institute for Mergers, Acquisitions and Alliances and the number of deals covered by the SDC Platinum M&A database over time. The data are annual observations from 1980 to 2018. The deals counts are expressed in thousands.

Panel A: Number of M&A Deals by Public Acquirers



Panel B: Number of M&A Deals by VC/PE-Financed Public Acquirers

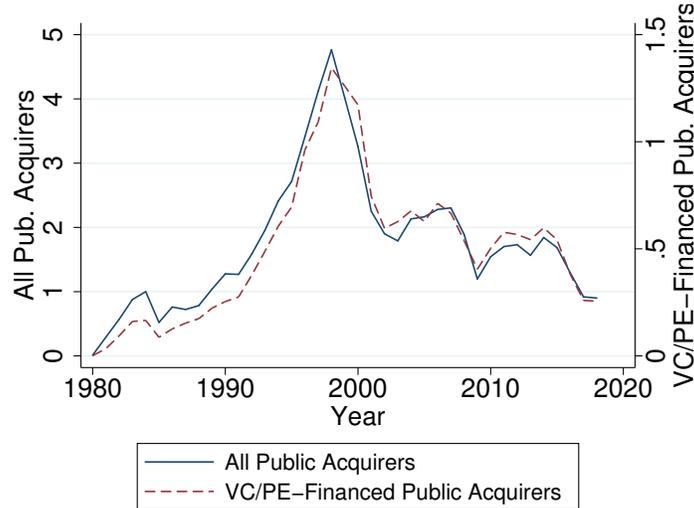


Fig. B.6. Number of M&A Deals by Public Acquirers

Figure shows the number of M&A deals with a public acquirer from the SDC Platinum M&A database over time. Panel B depicts the number of M&A deals with a public acquirer versus the number of M&A deals with a VC/PE-financed public acquirer. More details are provided in Appendix A.2. The data are annual observations from 1980 to 2018. The deals counts are expressed in thousands.

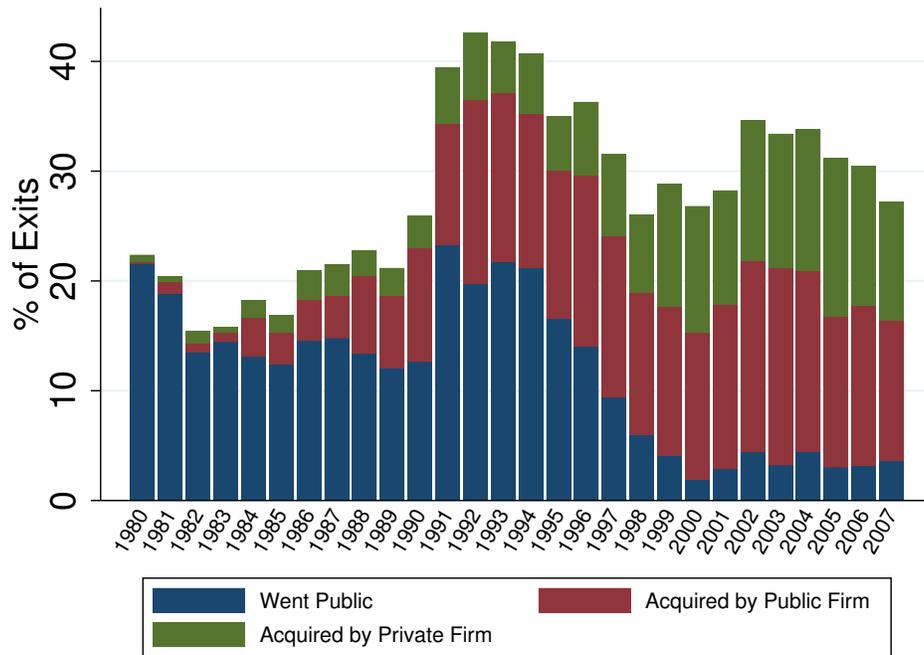


Fig. B.7. Exit Rate of VC/PE-Financed Private Firms

Figure shows the exit rates of VC/PE-financed private firms for each first financing year cohort. The exit state – went public, acquired by a public firm or acquired by a private firm – is measured ten years after the firm’s first round of financing for each cohort. The data are annual observations from 1980 to 2018. The exit rates are expressed in percentages.

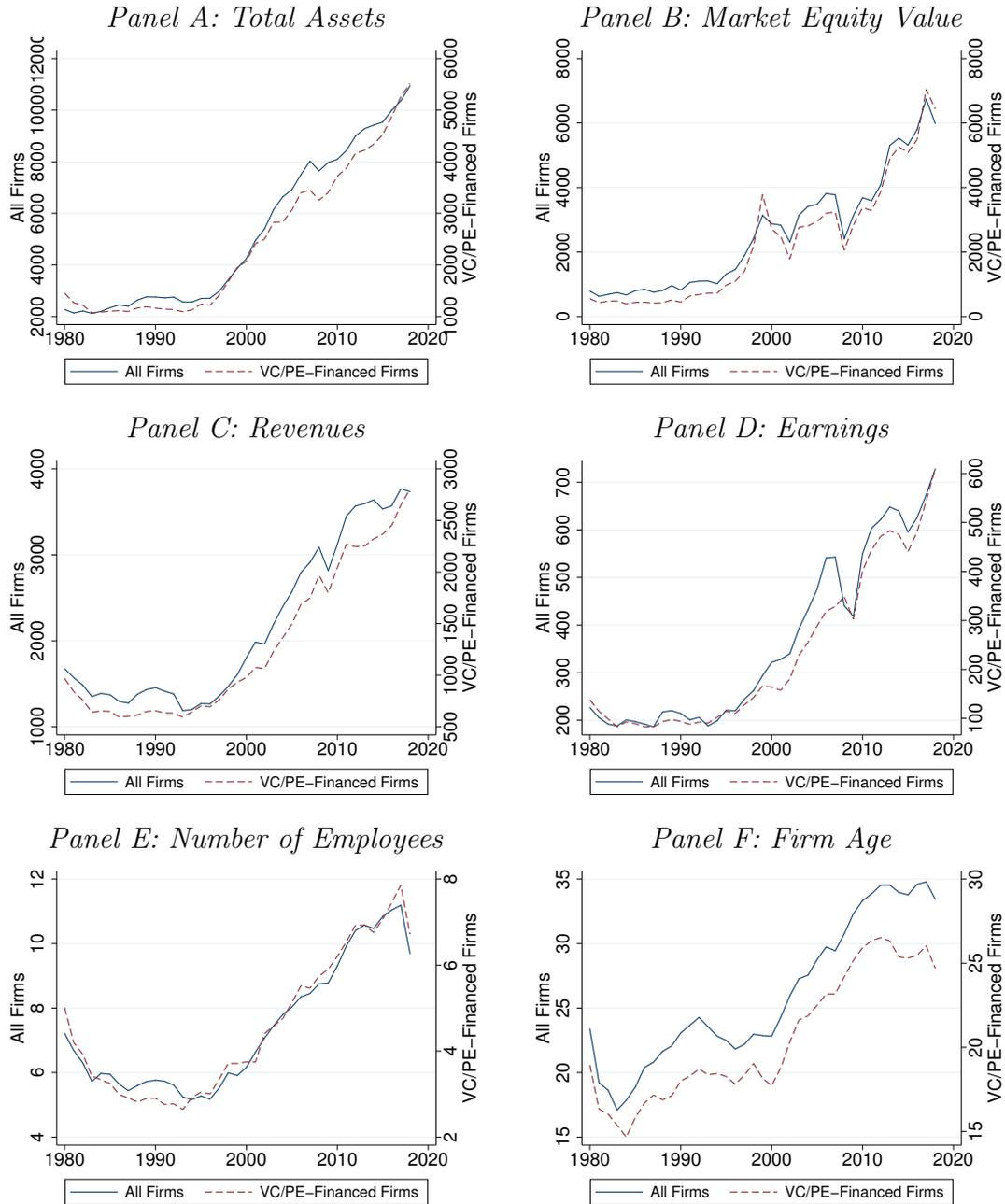


Fig. B.8. Average Size of Public Firms

Figure shows the cross-sectional mean size of all publicly listed U.S. firms (solid blue line) and of VC/PE-financed firms (dashed red line). The firm's size is measured with total assets, market value of equity, market value of firm, revenues, earnings, number of employees, and age. In Panels A - D, the data are real annual observations from 1980 to 2018, and are expressed in millions of December 2009 dollars. In Panel E, the data are annual observations, expressed in thousands. In Panel F, the data are annual observations, expressed in years.

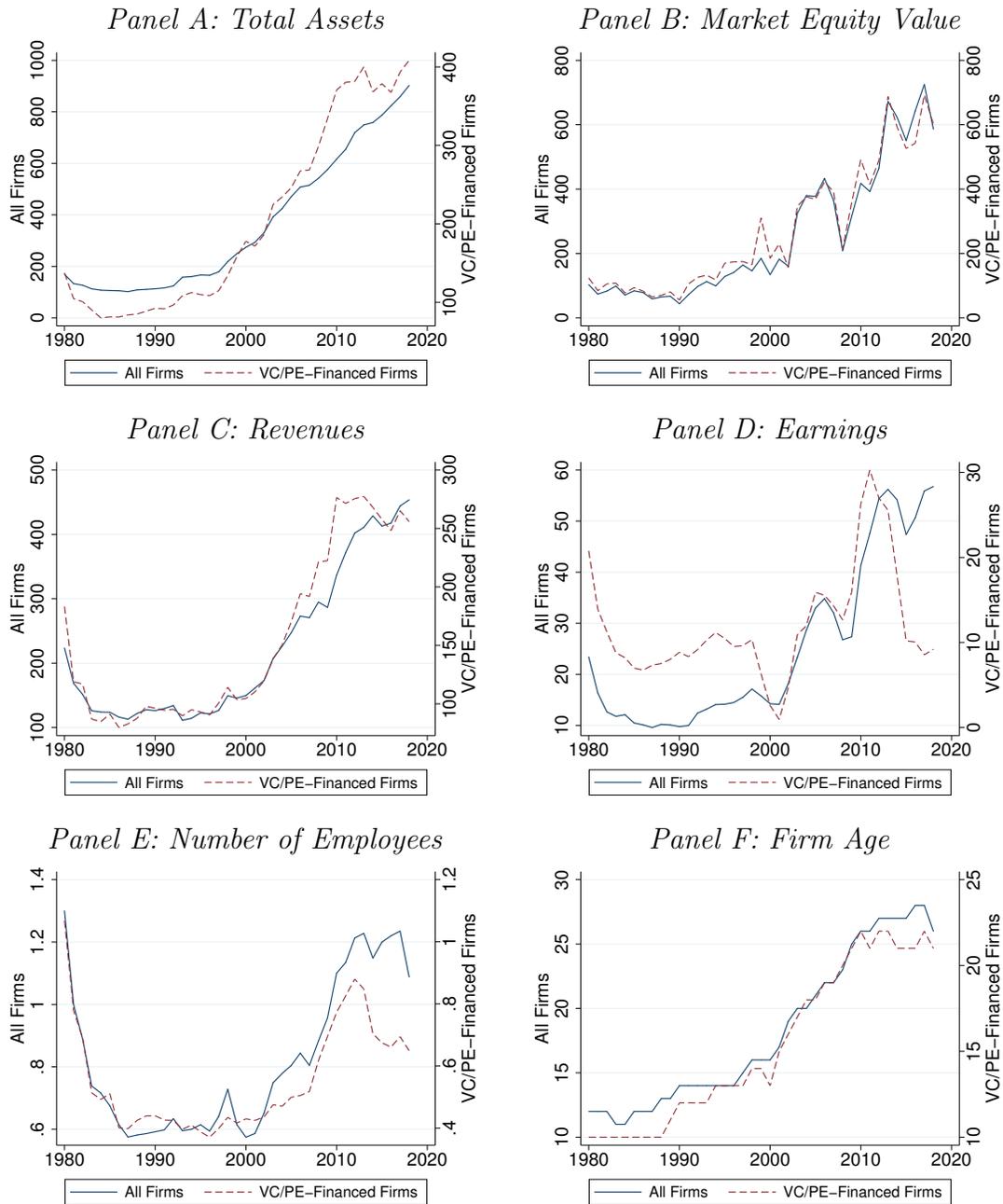


Fig. B.9. Median Size of Public Firms

Figure shows the cross-sectional median size of all publicly listed U.S. firms (solid blue line) and of VC/PE-financed firms (dashed red line). The firm's size is measured with total assets, market value of equity, market value of firm, revenues, earnings, number of employees, and age. In Panels A - D, the data are real annual observations from 1980 to 2018, and are expressed in millions of December 2009 dollars. In Panel E, the data are annual observations, expressed in thousands. In Panel F, the data are annual observations, expressed in years.

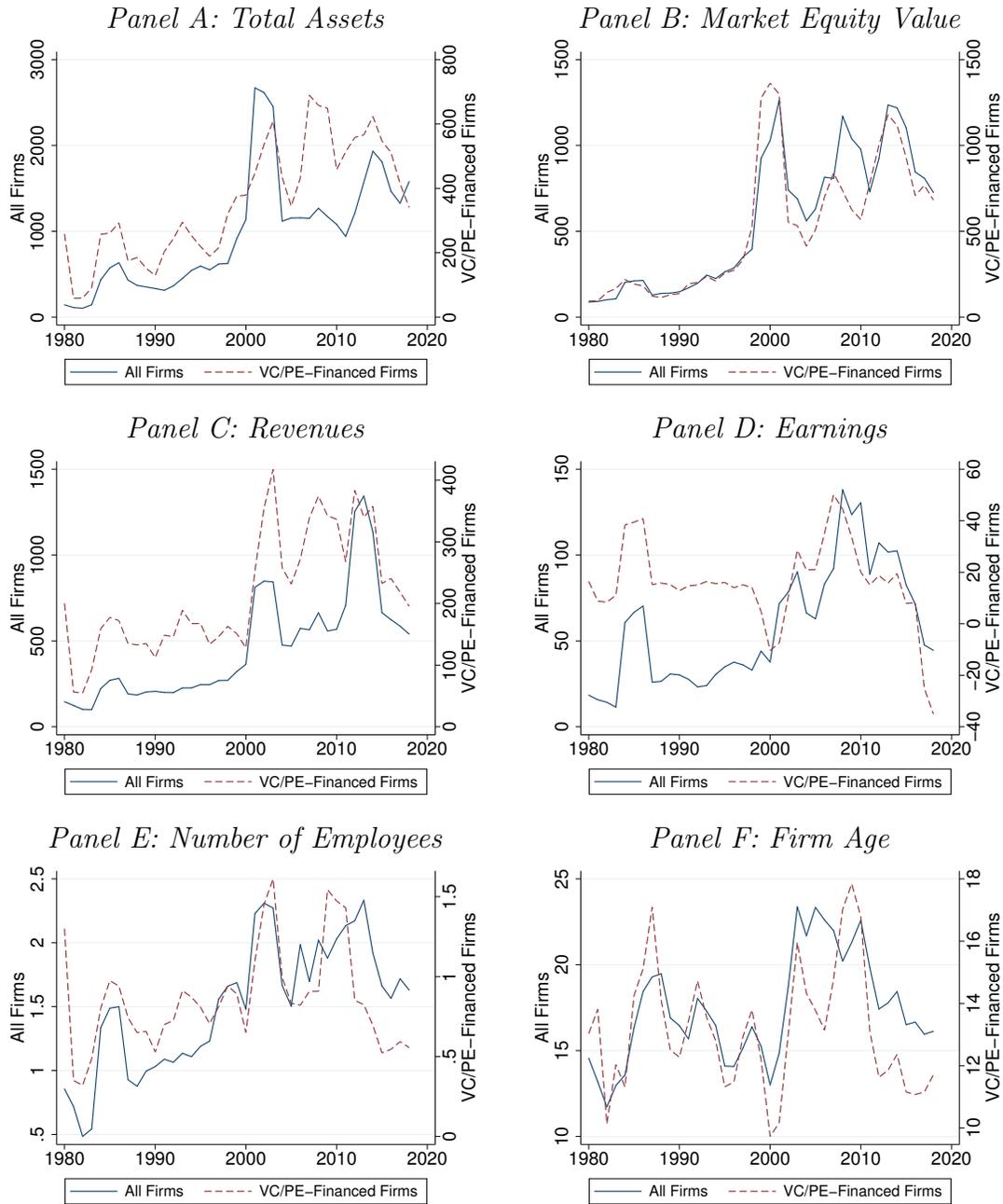


Fig. B.10. Average Size of Firms at IPO

The Figure shows the cross-sectional mean size of all firms at IPO (solid blue line) and of VC/PE-financed firms (dashed red line). The means are smoothed using the three-year moving average. The firm's size is measured with total assets, market value of equity, revenues, earnings, number of employees, and age. In Panels A - D, the data are real annual observations from 1980 to 2018, and are expressed in millions of December 2009 dollars. In Panel E, the data are annual observations, and are expressed in thousands. In Panel F, the data are annual observations, and are expressed in years.

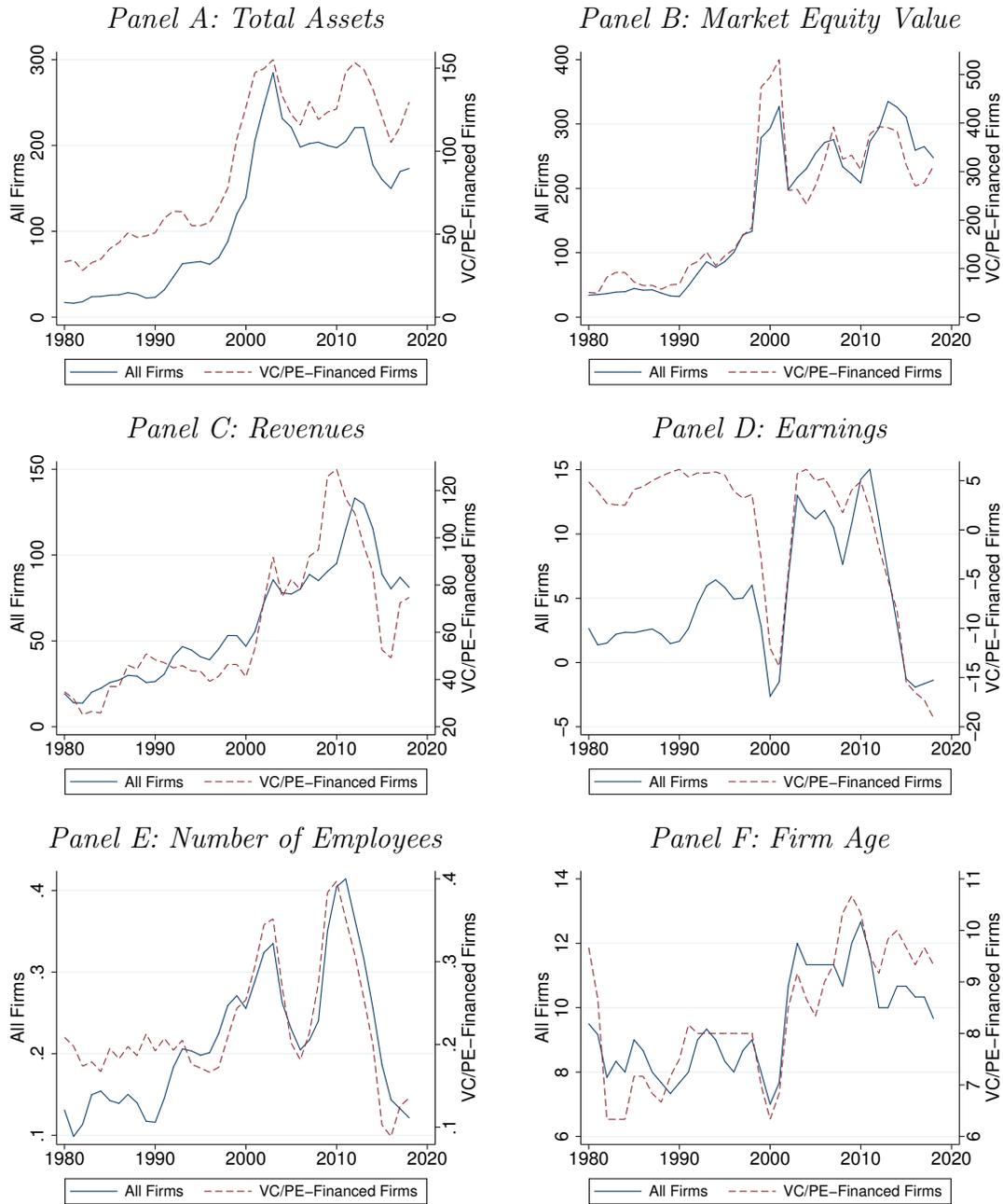


Fig. B.11. Median Size of Firms at IPO

The Figure shows the cross-sectional median size of all firms at IPO (solid blue line) and of VC/PE-financed firms (dashed red line). The medians are smoothed using the three-year moving average. The firm's size is measured with total assets, market value of equity, revenues, earnings, number of employees, and age. In Panels A - D, the data are real annual observations from 1980 to 2018, and are expressed in millions of December 2009 dollars. In Panel E, the data are annual observations, and are expressed in thousands. In Panel F, the data are annual observations, and are expressed in years.

Table B.1: Propensity to Go Public

		Early Period	Late Period	% Change
Number of public firms		7.16	3.80	-46.89
Number of private firms				
VenturExpert	VC/PE-financed firms			
	Failure 3 years after last financing round	10.11	14.90	47.36
	Failure 4 years after last financing round	10.40	15.92	53.02
	Failure 5 years after last financing round	10.79	16.90	56.57
	Failure 6 years after last financing round	11.25	17.82	58.36
	Failure 7 years after last financing round	11.78	18.71	58.83
Census	Firms with > 500 employees	8.54	14.81	73.37
IRS	C & S firms with assets>nominal \$50m	19.82	35.02	76.70
IRS	C & S firms with assets>real \$50m	24.51	33.61	37.15
IRS	C & S firms with assets>nominal \$100m	12.15	23.52	93.50
IRS	C & S firms with assets>real \$100m	15.19	22.53	48.33
IRS	C & S firms with revenues>nominal \$50m	17.43	33.56	92.50
IRS	C & S firms with revenues>real \$50m	25.25	31.09	23.14
Propensity to go public, %				
VenturExpert	VC/PE-financed firms			
	Failure 3 years after last financing round	72.47	25.53	-64.77
	Failure 4 years after last financing round	70.22	23.89	-65.98
	Failure 5 years after last financing round	67.36	22.51	-66.59
	Failure 6 years after last financing round	64.34	21.35	-66.82
	Failure 7 years after last financing round	61.25	20.34	-66.79
Census	Firms with > 500 employees	84.02	25.73	-69.38
IRS	C & S firms with assets>nominal \$50m	36.27	10.88	-69.99
IRS	C & S firms with assets>real \$50m	29.26	11.33	-61.27
IRS	C & S firms with assets>nominal \$100m	59.41	16.21	-72.72
IRS	C & S firms with assets>real \$100m	47.30	16.91	-64.26
IRS	C & S firms with revenues>nominal \$50m	41.33	11.37	-72.49
IRS	C & S firms with revenues>real \$50m	28.39	12.25	-56.85

The table reports the average counts of private U.S. firms and propensity to go public for the early period 1994-1998 and for the late period 2011-2015. The number of VC/PE-financed firms is calculated when the failure date is set to 3,4,5,6, and 7 years from the last financing round if a firm has not exited earlier via an IPO or acquisition (for additional information see Section 2). The number of private firms with more than 500 employees is calculated as the difference between the number of all firms with more than 500 employees reported by the Census Bureau and the number of all publicly listed firms. The number of private firms with assets/revenues above the certain threshold is calculated as the difference between the number of all firms assets/revenues above that threshold reported by the IRS and the number of publicly listed firms above that threshold. The firm counts are expressed in thousands, the propensity to go public and the changes between the early and late periods are expressed in percentages.

Table B.2: Propensity to Go Public — Adjusted for M&A

		Early Period	Late Period	% Change
Number of public firms		11.51	11.32	-1.66
Number of private firms				
VenturExpert	VC/PE-financed firms			
	Failure 3 years after last financing round	10.11	14.90	47.36
	Failure 4 years after last financing round	10.40	15.92	53.02
	Failure 5 years after last financing round	10.79	16.90	56.57
	Failure 6 years after last financing round	11.25	17.82	58.36
	Failure 7 years after last financing round	11.78	18.71	58.83
Census	Firms with > 500 employees	8.54	14.81	73.37
IRS	C & S firms with assets>nominal \$50m	19.82	35.02	76.70
IRS	C & S firms with assets>real \$50m	24.51	33.61	37.15
IRS	C & S firms with assets>nominal \$100m	12.15	23.52	93.50
IRS	C & S firms with assets>real \$100m	15.19	22.53	48.33
IRS	C & S firms with revenues>nominal \$50m	17.43	33.56	92.50
IRS	C & S firms with revenues>real \$50m	25.25	31.09	23.14
Propensity to go public, %				
VenturExpert	VC/PE-financed firms			
	Failure 3 years after last financing round	115.18	75.99	-34.03
	Failure 4 years after last financing round	111.69	71.11	-36.33
	Failure 5 years after last financing round	107.29	66.99	-37.56
	Failure 6 years after last financing round	102.62	63.55	-38.08
	Failure 7 years after last financing round	97.80	60.53	-38.11
Census	Firms with > 500 employees	134.66	76.56	-43.15
IRS	C & S firms with assets>nominal \$50m	58.02	32.39	-44.18
IRS	C & S firms with assets>real \$50m	46.89	33.72	-28.09
IRS	C & S firms with assets>nominal \$100m	94.83	48.23	-49.14
IRS	C & S firms with assets>real \$100m	75.69	50.31	-33.54
IRS	C & S firms with revenues>nominal \$50m	66.03	33.83	-48.77
IRS	C & S firms with revenues>real \$50m	45.50	36.46	-19.87

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Table B.3: Size of Public Firms and Firms at IPO

	All Firms			VC/PE-Financed Firms		
	Early	Late	% Change	Early	Late	% Change
Size of public firms						
Log(Total assets) [†]	5.31 (2.11)	6.60 (2.15)	24.12***	5.01 (1.89)	6.14 (2.06)	22.38***
Log(Market value of firm) [†]	5.40 (2.03)	6.63 (2.10)	22.87***	5.43 (1.80)	6.55 (1.97)	20.67***
Log(Market equity value) [†]	5.07 (2.00)	6.28 (2.11)	24.03***	5.20 (1.76)	6.33 (1.96)	21.60***
Log(Revenues) [†]	4.88 (2.22)	5.88 (2.38)	20.40***	4.59 (2.13)	5.47 (2.38)	19.21***
Log(Earnings) [†]	3.40 (2.07)	4.58 (2.12)	34.58***	3.29 (1.90)	4.50 (2.10)	37.04***
Number of employees [†]	5.43 (24.05)	10.44 (49.37)	92.44***	3.22 (11.01)	6.85 (24.30)	112.64***
Age [†]	22.44 (22.44)	34.13 (26.70)	52.06***	18.38 (18.04)	25.94 (19.37)	41.17***
Size of public firms at IPO						
Log(Total assets)	3.91 (1.78)	5.43 (1.74)	38.87***	4.03 (1.42)	5.02 (1.37)	24.52***
Log(Market value of firm)	4.40 (1.51)	5.83 (1.50)	32.46***	4.78 (1.31)	5.87 (1.29)	22.69***
Log(Market equity value)	4.19 (1.47)	5.58 (1.46)	33.11***	4.64 (1.30)	5.76 (1.29)	24.15***
Log(Revenues)	3.31 (2.26)	4.43 (2.31)	34.01***	3.39 (2.05)	3.98 (2.19)	17.23***
Log(Earnings)	2.23 (1.75)	3.52 (1.75)	57.61***	2.31 (1.42)	3.25 (1.64)	40.66***
Number of employees	1.17 (6.66)	1.90 (6.47)	61.77***	0.77 (2.76)	0.87 (2.63)	13.26
Age	16.24 (20.57)	19.41 (25.06)	19.51***	13.27 (17.02)	12.90 (16.06)	-2.76

The table reports the changes in (i) the average size of all public firms and VC/PE-financed public firms for the early period 1994-1998 and for the late period 2011-2015 (marked with †); (ii) the average of size of all and VC/PE-financed firms at the IPO date for the early period 1980-1998 and for the late period 2001-2015. Standard deviations are reported in the parentheses. The firm's size is measured with total assets, market value of firm, market value of equity, market value of firm, revenues, earnings, number of employees, and age. The data are real annual observations, and are expressed in millions of December 2009 dollars, except for the number of employees and age. The number of employees is expressed in thousands, and age is expressed in years. The changes in firm's size between the early and late periods are expressed in percentages. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

C Proofs of Propositions

In this Appendix, we provide proofs for the propositions in the main text.

C.1 Private and Public Firm Values (Proposition 1)

C.1.1 Private Firm Value

The value of a private firm, $v_{priv}(x; \theta)$, satisfies the ODE:

$$(r + \theta + \lambda)v_{priv}(x; \theta) = \mu x \frac{\partial v_{priv}(x; \theta)}{\partial x} + \frac{\sigma^2}{2} x^2 \frac{\partial^2 v_{priv}(x; \theta)}{\partial x^2} + (1 - \tau)(\mathcal{A}_{priv}(\theta)x^b - c_f), \quad (24)$$

where $b = \frac{1}{1-\alpha}$ and

$$\mathcal{A}_{priv}(\theta) = (1 - \alpha) \left(\frac{\alpha}{\frac{r+\theta}{1-\tau} + \delta} \right)^{\frac{\alpha}{1-\alpha}}. \quad (25)$$

The solution to the associated homogeneous ODE has the general form:

$$v_{priv}(x; \theta) = A_1 x^{\gamma_1} + A_2 x^{\gamma_2} \quad (26)$$

where γ_1 and γ_2 are roots of the fundamental quadratic, given by

$$\gamma_1 = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r + \theta + \lambda)}{\sigma^2}}, \quad \gamma_2 = \frac{1}{2} - \frac{\mu}{\sigma^2} - \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r + \theta + \lambda)}{\sigma^2}}, \quad (27)$$

with $\gamma_1 > 1$ and $\gamma_2 < 0$. The inhomogeneous portion has a particular solution of the form

$$\frac{(1 - \tau)\mathcal{A}_{priv}(\theta)x^b}{r + \theta + \lambda - \mu b - \frac{\sigma^2}{2}b(b - 1)} - \frac{(1 - \tau)c_f}{r + \theta + \lambda}. \quad (28)$$

Combining, we have a solution of the form

$$v_{priv}(x; \theta) = A_1 x^{\gamma_1} + A_2 x^{\gamma_2} + (1 - \tau) \left(\frac{\mathcal{A}_{priv}(\theta)x^b}{r + \theta + \lambda - \mu b - \frac{\sigma^2}{2}b(b - 1)} - \frac{c_f}{r + \theta + \lambda} \right) \quad (29)$$

where A_1 and A_2 are solved for by imposing the boundary conditions. We assume that when a private firm exits, it receives zero recovery. Optimal exercise of the exit and IPO options

implies the following four boundary conditions:

$$v_{priv}(x_{D,priv}; \theta) = 0 \quad (30)$$

$$\frac{\partial v_{priv}(x_{D,priv}; \theta)}{\partial x} = 0 \quad (31)$$

$$v_{priv}(\bar{x}_{IPO}; \theta) = v_{pub}(\bar{x}_{IPO}) - \mathcal{I}_{IPO} \quad (32)$$

$$\frac{\partial v_{priv}(\bar{x}_{IPO}; \theta)}{\partial x} = \frac{\partial v_{pub}(\bar{x}_{IPO})}{\partial x} \quad (33)$$

Equations (30) and (31) are the value matching and smooth pasting conditions for the optimal abandonment threshold, $x_{D,priv}$. Equations (32) and (33) are the value matching and smooth pasting conditions for the optimal IPO threshold, \bar{x}_{IPO} . These four equations are solved for the four unknowns: $x_{D,priv}$, \bar{x}_{IPO} , A_1 , and A_2 .

C.1.2 Public Firm Value

Public firm value satisfies the ODE:

$$(r + \lambda)v_{pub}(x) = \mu x \frac{\partial v_{pub}(x)}{\partial x} + \frac{\sigma^2}{2} x^2 \frac{\partial^2 v_{pub}(x)}{\partial x^2} + (1 - \tau)(\mathcal{A}_{pub}x^b - c_f) - \mathcal{C}_{pub}, \quad (34)$$

The public firm value has solution of the form

$$v_{pub}(x) = B_1 x^{\xi_1} + B_2 x^{\xi_2} + (1 - \tau) \left(\frac{\mathcal{A}_{pub} x^b}{r_{pub} + \lambda - \mu b - \frac{\sigma^2}{2} b(b-1)} - \frac{c_f}{r_{pub} + \lambda} - \frac{\mathcal{C}_{pub}}{(1 - \tau)(r_{pub} + \lambda)} \right), \quad (35)$$

where ξ_1 and ξ_2 are roots of the fundamental quadratic, given by

$$\xi_1 = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r + \lambda)}{\sigma^2}}, \quad \xi_2 = \frac{1}{2} - \frac{\mu}{\sigma^2} - \sqrt{\left(\frac{\mu}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2(r + \lambda)}{\sigma^2}}, \quad (36)$$

with $\xi_1 > 1$ and $\xi_2 < 0$. The B coefficients and exit threshold $x_{D,priv}$ are determined by the boundary conditions. To ensure the valuation is bounded, we require the coefficient on the positive root, B_1 , to be set to zero. Public firm value is then given by

$$v_{pub}(x) = B_2 x^{\xi_2} + (1 - \tau) \left(\frac{\mathcal{A}_{pub} x^b}{r + \lambda - \mu b - \frac{\sigma^2}{2} b(b-1)} - \frac{c_f}{r_{pub} + \lambda} - \frac{\mathcal{C}_{pub}}{(1 - \tau)(r + \lambda)} \right). \quad (37)$$

We assume that a public firm can choose to exit public markets, in which case it receives a fraction of the future cash flows. The following two boundary conditions determine B_2 and $x_{D,pub}$:

$$v_{pub}(x_{D,pub}) = \varrho \frac{(1 - \tau)\mathcal{A}_{pub}x_{D,pub}^b}{r + \lambda - \mu b - \frac{\sigma^2}{2}b(b - 1)}, \quad (38)$$

$$\frac{\partial v_{pub}(x_{D,pub})}{\partial x} = b\varrho \frac{(1 - \tau)\mathcal{A}_{pub}x_{D,pub}^{b-1}}{r + \lambda - \mu b - \frac{\sigma^2}{2}b(b - 1)}. \quad (39)$$

Plugging in and rearranging gives

$$B_2x_{D,pub}^{\xi_2} + (1 - \tau) \left(\frac{(1 - \varrho)\mathcal{A}_{pub}x_{D,pub}^b}{r + \lambda - \mu b - \frac{\sigma^2}{2}b(b - 1)} - \frac{c_f}{r + \lambda} - \frac{\mathcal{C}_{pub}}{(1 - \tau)(r + \lambda)} \right) = 0, \quad (40)$$

$$\xi_2 B_2 x_{D,pub}^{\xi_2 - 1} + (1 - \tau) \frac{(1 - \varrho)b\mathcal{A}_{pub}x_{D,pub}^{b-1}}{r + \lambda - \mu b - \frac{\sigma^2}{2}b(b - 1)} = 0. \quad (41)$$

These two nonlinear equations can be solved for the two unknowns, B_2 and $x_{D,pub}$.

C.2 Derivation of Private Firm Distribution (Proposition 2)

Define $z \equiv \log(x)$. By applying Itô's Lemma, z evolves as an arithmetic Brownian motion given by

$$dz_t = \left(\mu - \frac{1}{2}\sigma^2 \right) dt + \sigma dW_t. \quad (42)$$

Let $\phi(z)$ denote the stationary distribution of log productivity for private firms. Firms exogenously exit at rate λ . A new private firm can choose to enter by paying a cost c_{entry} and draws its initial log cash flow from a distribution denoted $g(x)$. We assume that the distribution of initial cash flows of private firms entrants is uniform: $x_0 \sim U[x_A, x_B]$, where $x_{D,priv} < x_B < \bar{x}_{IPO}$. This implies that the log cash flow distribution of private firm entrants is exponentially distributed over the interval $[x_A, x_B]$:

$$h(x) = e^{z - \hat{z}}, \quad (43)$$

where $\hat{z} = \log(x_B - x_A)$. To solve for the stationary distribution of log productivity, $\phi(z)$, we consider three regions: $z \in (z_{D,priv}, z_A)$; $z \in (z_A, z_B)$; $z \in (z_B, \bar{z}_{IPO})$.

Region 1: $z \in (z_{D,priv}, z_A)$

Over this interval, firms exit at rate λ , however there is no flow of new entrants. The Kolmogorov forward equation (KFE) characterizing the steady state distribution for this region satisfies

$$\frac{1}{2}\sigma^2\phi_{zz}(z) - \left(\mu - \frac{1}{2}\sigma^2\right)\phi_z(z) - \lambda\phi(z) = 0. \quad (44)$$

This has the general solution

$$\phi(z) = C_1e^{\beta_1z} + C_2e^{\beta_2z}, \quad (45)$$

where β_1 and β_2 are the roots of the fundamental quadratic,

$$\beta = \frac{\mu}{\sigma^2} - \frac{1}{2} \pm \frac{\sqrt{2\lambda\sigma^2 + (\mu - \sigma^2/2)^2}}{\sigma^2} \quad (46)$$

and where $\beta_1 > 0 > \beta_2$. The coefficients C_1 and C_2 are solved below.

Region 2: $z \in (z_A, z_B)$

In this region, firms exit at rate λ due to the death shock and a flow of new firms enter with initial log cash flows given by the distribution $h(z)$. Over this region, the stationary distribution $\phi(z)$ satisfies the KFE:

$$\frac{1}{2}\sigma^2\phi_{zz}(z) - \left(\mu - \frac{1}{2}\sigma^2\right)\phi_z(z) - \lambda\phi(z) + h(z) = 0. \quad (47)$$

This has the general solution

$$\phi(z) = D_1e^{\beta_1z} + D_2e^{\beta_2z} + D_3e^z, \quad (48)$$

where β_1 and β_2 are the same roots of the fundamental quadratic given in Equation (46) of region 1 above. We can solve for D_3 , the coefficient on the particular solution of the KFE, by plugging in:

$$\frac{1}{2}\sigma^2D_3e^z - (\mu - \frac{1}{2}\sigma^2)D_3e^z - \lambda D_3e^z + e^{z-\hat{z}} = 0. \quad (49)$$

This can be rearranged as

$$D_3 = \frac{e^{-\hat{z}}}{\lambda + (\mu - \frac{1}{2}\sigma^2) - \frac{1}{2}\sigma^2}, \quad (50)$$

which gives a general solution in this case of

$$\phi(z) = D_1 e^{\beta_1 z} + D_2 e^{\beta_2 z} + \frac{e^{z-\hat{z}}}{\lambda + (\mu - \frac{1}{2}\sigma^2) - \frac{1}{2}\sigma^2}. \quad (51)$$

The coefficients D_1 and D_2 are solved by imposing the boundary conditions given below.

Region 3: $z \in (z_B, \bar{z}_{IPO})$

As in region 1, firms in this region exit at rate λ and there is no new entry in this region, so we have the same ODE characterizing the KFE. That is, the KFE satisfies

$$\frac{1}{2}\sigma^2 \phi_{zz}(z) - \left(\mu - \frac{1}{2}\sigma^2\right) \phi_z(z) - \lambda \phi(z) = 0, \quad (52)$$

and the general solution is given by

$$\phi(z) = H_1 e^{\beta_1 z} + H_2 e^{\beta_2 z}, \quad (53)$$

where again the coefficients H_1 and H_2 are solved for by imposing the appropriate boundary conditions.

We have a total of six boundary conditions for the stationary distribution of log productivity of private firms, $\phi(z)$:

$$\phi(z_D) = 0 \quad (54)$$

$$\phi(\bar{z}_{IPO}) = 0 \quad (55)$$

$$\lim_{z \uparrow z_A} \phi(z) = \lim_{z \downarrow z_A} \phi(z) \quad (56)$$

$$\lim_{z \uparrow z_A} \phi_z(z) = \lim_{z \downarrow z_A} \phi_z(z) \quad (57)$$

$$\lim_{z \uparrow z_B} \phi(z) = \lim_{z \downarrow z_B} \phi(z) \quad (58)$$

$$\lim_{z \uparrow z_B} \phi_z(z) = \lim_{z \downarrow z_B} \phi_z(z). \quad (59)$$

Equations (54) and (55) follow from the fact that private firms exit when their log productivity falls to $z_{D,priv}$ and choose to go public when their log productivity reaches the IPO threshold \bar{z}_{IPO} . Equations (56)–(59) ensure sufficient smoothness for $\phi(z)$. These six

boundary conditions determine the six coefficients, $C_1, C_2, D_1, D_2, H_1, H_2$.

The stationary distribution of private firm log productivity, $\phi(z)$, is given by

$$\phi(z) = \begin{cases} C_1 e^{\beta_1 z} + C_2 e^{\beta_2 z}, & \text{if } z_{D,priv} < z < z_A \\ D_1 e^{\beta_1 z} + D_2 e^{\beta_2 z} + \frac{e^{z-\bar{z}}}{\lambda + (\mu - \frac{1}{2}\sigma^2) - \frac{1}{2}\sigma^2}, & \text{if } z_A \leq z \leq z_B \\ H_1 e^{\beta_1 z} + H_2 e^{\beta_2 z}, & \text{if } z_B < z < \bar{z}_{IPO}. \end{cases} \quad (60)$$

For the level of productivity, x , the stationary distribution of private firms, $\varphi(x)$, can be expressed as

$$\varphi(x) = \begin{cases} C_1 x^{\beta_1 - 1} + C_2 x^{\beta_2 - 1}, & \text{if } x_{D,priv} < x < x_A \\ D_1 x^{\beta_1 - 1} + D_2 x^{\beta_2 - 1} + \frac{1}{(x_B - x_A)(\lambda + (\mu - \frac{1}{2}\sigma^2) - \frac{1}{2}\sigma^2)}, & \text{if } x_A \leq x \leq x_B \\ H_1 x^{\beta_1 - 1} + H_2 x^{\beta_2 - 1}, & \text{if } x_B < x < \bar{x}_{IPO}, \end{cases} \quad (61)$$

C.3 Derivation of Public Firm Distribution (Proposition 3)

As with the private firm distribution, it is easier to work with the log productivity. Again, let $z \equiv \log(x)$ and let $\psi(z)$ denote the stationary distribution of log productivity of public firms. This distribution satisfies the KFE

$$\frac{1}{2}\sigma^2 \psi_{zz}(z) - \left(\mu - \frac{1}{2}\sigma^2\right) \psi_z(z) - \lambda \psi(z) = 0, \quad (62)$$

for $z \neq \bar{z}_{IPO}$. The general solution is given by

$$\psi(z) = \begin{cases} J_1 e^{\zeta_1 z} + J_2 e^{\zeta_2 z}, & \text{if } z_{D,pub} < z < \bar{z}_{IPO} \\ K_1 e^{\zeta_1 z} + K_2 e^{\zeta_2 z}, & \text{if } z > \bar{z}_{IPO}, \end{cases} \quad (63)$$

where ζ_1 and ζ_2 are the roots of the fundamental quadratic,

$$\zeta = \frac{\mu}{\sigma^2} - \frac{1}{2} \pm \frac{\sqrt{2\lambda\sigma^2 + (\mu - \sigma^2/2)^2}}{\sigma^2}, \quad (64)$$

with $\zeta_1 > 0 > \zeta_2$. The coefficients J_1 , J_2 , K_1 , and K_2 are determined by imposing the following conditions:

$$\int_{\bar{x}}^{\infty} \psi(x) < \infty \quad (65)$$

$$J_1 e^{\zeta_1 z_{D,pub}} + J_2 e^{\zeta_2 z_{D,pub}} = 0 \quad (66)$$

$$J_1 e^{\zeta_1 \bar{z}_{IPO}} + J_2 e^{\zeta_2 \bar{z}_{IPO}} = K_2 e^{\zeta_2 \bar{z}_{IPO}} \quad (67)$$

$$\lambda \Upsilon_{IPO} \left(\int_{z_{D,pub}}^{\infty} \psi(z) dz \right) - \frac{1}{2} \sigma^2 \Upsilon_{IPO} \psi'(z_{D,pub}) = \Upsilon_{IPO} \quad (68)$$

Equation (65) ensures that $\psi(z)$ is integrable as $z \rightarrow \infty$, which implies $K_1 = 0$. Equation (66) states that there is zero mass of public firms at the optimal exit boundary, $z_{D,pub}$ and equation (67) ensures continuity of $\psi(z)$ at the IPO entry point, \bar{z}_{IPO} .

Equation (68) follows from the definition of a steady state distribution of public firms. In steady state, the flow of exit is equal to the flow of entry. The mass of public firms, Q_{public} , can be expressed as

$$Q_{public} = \Upsilon_{IPO} \left(\int_{z_{D,pub}}^{\infty} \psi(z) dz \right). \quad (69)$$

Of the existing mass of public firms, a fraction λ exit due to the Poisson shock. Additionally, some public firms exit by hitting the lower bound of cash flows, $z_{D,pub}$, at which they optimally abandon. The flow of firms hitting this lower threshold $z_{D,pub}$ is given by

$$-\frac{1}{2} \sigma^2 \Upsilon_{IPO} \psi'(z_{D,pub}). \quad (70)$$

Together, these two forms of exit account for the left hand side of Equation (68). This flow of exit must be equal to the inflow of public firms, which is the flow of private firms exercising their IPO option, Υ_{IPO} .

So the stationary distribution of public firm log cash flows is given by $\Upsilon_{IPO} \times \psi(z)$, where

$$\psi(z) = \begin{cases} J_1 e^{\zeta_1 z} + J_2 e^{\zeta_2 z}, & \text{if } z_{D,pub} < z < \bar{z}_{IPO} \\ K_2 e^{\zeta_2 z}, & \text{if } z > \bar{z}_{IPO} \end{cases} \quad (71)$$

The distribution of the level of productivity x for public firms is given by $\Upsilon_{IPO} \times \Psi(x)$, where

$$\Psi(x) = \begin{cases} J_1 x^{\zeta_1 - 1} + J_2 x^{\zeta_2 - 1}, & \text{if } x_{D, pub} < x < \bar{x}_{IPO} \\ K_2 x^{\zeta_2 - 1}, & \text{if } x > \bar{x}_{IPO} \end{cases} \quad (72)$$

Chapters 2 and 3

Trade Credit as an Exertion of Market Power

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Abstract

I investigate why large financially unconstrained firms delay payment to small financially constrained suppliers. I show theoretically that large firms can use payment delays as a tool to constrain the supplier's ability to fund production for rival customers and therein reduce competition. Empirically, I obtain a new inter-firm credit dataset to test the theory's main predictions on how financial constraints, bargaining power, and product substitutability should determine payment delays. In addition to examining equilibrium relationships, I exploit a government program as an exogenous shock to supplier financial constraints. The empirical results support the theoretical predictions.

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1 Introduction

Trade credit is a large source of short-term financing in which customers delay payment to their suppliers. Traditional trade credit theories explain why financially *constrained* customers can borrow more cheaply from their suppliers than from financial institutions. However, there is growing empirical evidence of the reverse. Large *unconstrained* customers often borrow from their smaller, more constrained suppliers, despite having cheaper access to financing elsewhere.²

The media suggests that large customers use their market power to delay payment, prompting concerns for anti-trust authorities.³ However, the trade credit literature criticizes this argument. Since small constrained suppliers have a high cost of capital, large unconstrained firms should be able to pay sooner and receive a price discount in excess of their own cost of capital. Accordingly, the literature argues that large customers should exert market power purely in the form of a price discount, not at all through delayed payment, and provides a few alternative rationalizations for their behavior.⁴

Using a new dataset containing bilateral trade credit relationships between thousands of customers and their suppliers, I propose and test a new theory. I conjecture that a large customer can use trade credit to reduce output market competition. In taking trade credit, large firms force suppliers to obtain costly external financing in order to continue to produce for rival customers. As a result, rivals' costs increase and output decrease. Importantly, while this theory is not the first attempt to explain why large firms delay payment, it is the first to conclude that their behavior is actually anti-competitive.

To generate empirical predictions, I build upon buyer power models in the industrial organization literature (Horn and Wolinsky 1988; Inderst and Wey 2007; Chen 2019) and develop a model of a vertical supply relationship. I consider a two period model with a single supplier that produces for two competing retailers, where one retailer is large and has bargaining power and the other is small and does not. Bargaining occurs sequentially, first with the large retailer and then with the small retailer, and is via Nash bargaining. Firms bargain over contracts that consist of a price, quantity, and delayed payment. After bargaining, firms raise external financing to cover any costs in excess of internal funds available. The equilibrium consists of two supply contracts and each firm's external financing.

To show the key ways that my theory departs from the traditional theory, I formulate a few benchmark models. Starting with a frictionless benchmark, I show that firms are

²Klapper et. al. (2012); Murfin and Njoroge (2015); Barrot (2016); Breza and Liberman (2017); Giannetti et. al. (2021)

³See for example New York Times article: "Big Companies Pay Later, Squeezing Their Suppliers". <https://www.nytimes.com/2015/04/07/business/big-companies-pay-later-squeezing-their-suppliers.html>

Also see: <https://www.businesswire.com/news/home/20210512005058/en/Late-payments-by-large-firms-are-%E2%80%98deliberate%E2%80%99-and-harm-recovery-say-small-businesses>

⁴Dass, Kale, and Nanda (2015); Liang and Sudbury (2019); Giannetti et. al. (2021)

indifferent towards payment timing. I next formulate the standard benchmark, which adds supplier financial constraints to frictionless benchmark. The standard benchmark represents traditional trade credit theory, which predicts that unconstrained retailers should not delay payment to constrained suppliers. The fact that unconstrained retailers pay constrained suppliers late is at odds with the traditional theory and is what this theory attempts to explain.

The objectives of the model are to show that this theory can generate payment delays between an unconstrained retailer and constrained supplier and identify a set of testable predictions. I show that there are two necessary conditions—the retailer must have high bargaining power relative to the supplier’s other customers and the retailer must compete with the supplier’s other customers.

The theory makes several testable predictions. The first is that this theory aligns with traditional theories regarding pairwise financial constraints—trade credit should flow from relatively less constrained suppliers to relatively more constrained customers. Additionally, trade credit should decrease in rivals’ financial constraints. The next prediction comes from the necessary condition in the last paragraph. For unconstrained customers, trade credit should increase in the customer’s bargaining power *relative* to the supplier’s other customers. This differs from other papers that study the connection between trade credit and bargaining power as these focus on the customer’s bargaining power with the supplier in absolute terms. This theory suggests that prior results on the positive relationship between trade credit and bargaining power in absolute terms are actually driven by bargaining power in relative terms. Next, the model makes predictions on the effects of product substitutability on trade credit. The model predicts that the effect should be positive for high bargaining power customers and negative for low bargaining power customers.

Lastly, the model makes a set of predictions on how payment delays should respond to a supplier cash flow shock. These involve the relative strength of the response based on financial constraints, bargaining power, and product substitutability. Payment delays should increase when the supplier experiences stronger financial frictions and customer experiences weaker financial frictions. Additionally, for high bargaining power customers, the response should be stronger when competition is lower. For low bargaining power customers, however, the response should be stronger when competition is higher.

In order to test predictions, I obtain a novel trade credit dataset from Experian. The dataset contains inter-firm current and overdue credit balances on matched U.S. customer-supplier firm pairs from 2008-2016. Importantly, many datasets report inter-firm credit at the aggregate customer or supplier level, yet very few report this variable between matched customer-supplier firm pairs. This level of detail is necessary to test empirical predictions that involve heterogeneity in payment timing across customers of

the same supplier or suppliers of the same customer.

Using this dataset, I create measures of delinquent payment and center the empirical analysis around determinants of delinquency. I start the empirical analysis by documenting a set of facts. First, I use the data to re-examine the motivating fact of this paper—that large firms delay payment to small suppliers. I find a positive relationship between delinquency and customer size. This relationship is surprising in the context of traditional trade credit theories, which predict that customers should pay more promptly as their financial constraints loosen.

Next, I examine the relationship between delinquency and bargaining power as a means of reconciling the size pattern. I document a positive relationship, suggesting that bargaining power has the potential to explain the size pattern through a positive effect of size on trade credit via bargaining power that counteracts a negative effect of size on trade credit via financial constraints. Importantly, the type of bargaining power that my theory on is the customer's bargaining power relative to rivals, while the literature typically focuses on the customer's bargaining power relative to the supplier. Comparing my bargaining power measure with the literature's, I show that the relationship with my measure is more aligned with the size pattern. Lastly, I examine the connection between bargaining power and product substitutability in determining trade credit. Consistent with the model, I show that gap between high and low bargaining power customers widens as product substitutability increases.

The simple plots provide suggestive evidence of the theory's predictions, control for a wide variety of omitted variables. Because I have matched customer-supplier level data, I am able to include layers of fixed effects that aren't possible with only firm level data. My primary specification of fixed effects includes a triple interaction of supplier, customer's industry, and time. This controls for the supplier's cost of providing credit to a customer's industry and the customer industry's demand for credit from the supplier. My secondary specification of fixed effects includes an interaction of supplier and time and an interaction of customer and time. This controls for any factor that might affect the supplier's cost of providing credit to all customers and a customer's demand for credit from all suppliers. I generally find support for the model's implications.

I conduct an additional empirical exercise to test if changes in delinquency are consistent with the model's predictions. Specifically, I consider an arguably exogenous shock to supplier internal funds, stemming from a 2011 reform that required the federal government to pay its own suppliers sooner. I examine how customers changed their payment behavior towards treated relative to untreated suppliers before and after the reform. The basic result is that customers paid treated suppliers later. As a second result, I find that the effect was strongest in the sub-sample of customer-supplier pairs with constrained suppliers and unconstrained customers. Although the second result may seem counter-intuitive, it is consistent with the model predictions.

Next, I examine the role of bargaining power. I confine the analysis to treated suppliers and test the response of high bargaining power customers relative to low bargaining power customers after the reform. I find that high bargaining power customers paid later than low bargaining power customers after the reform.

The results from this exercise not only provide empirical support for my theory's predictions, but also important standalone policy implications. They show that government aid can constitute a credit shock that propagates through the firm production network and that large firms may be the ultimate recipients of the aid intended for small one. This raises a broader question of whether or not large firms use their bargaining power to extract the benefits of a wide variety of government aid (such as grants, tax credits, or loan guarantees) via supply contracts.

2 Literature

This paper contributes to several strands of literature. In broad terms, this paper studies the role of industrial organization in financing decisions. One group of related papers focuses on horizontal product market competition, stemming from Brander and Lewis (1986), and examines the relationship between competition with financing variables such as the cost of debt (Valta 2012) and capital structure (Xu 2012). Another focuses on vertical contracting (Chu 2012; Hennessey and Livdan 2009; Campello and Gao 2017; Banerjee et. al. 2008). My paper combines these two groups—horizontal product market competition and vertical contracting—in studying how firms use the trade credit feature of vertical supply contracts to influence horizontal competition.

Topically, this paper contributes to the trade credit literature. The bulk of the trade credit literature proposes and tests theories for why trade credit exists and attempts to explain why a supplier may have a lending advantage to a customer relative to a financial institution. Such explanations include, but are not limited to, transaction costs (Ferris 1981), information asymmetry (Biais and Gollier 1987; Smith 1987), collateral value of goods (Frank and Maksimovic 2008; Fabbri and Menichini 2010), moral hazard (Kim and Shin 2012; and Burkart and Ellingsen 2004), and price discrimination (Brennan et. al. 1988).

More specifically, this paper fits in growing literature on the connection between trade credit and competition. Empirically, several studies have examined the relationship between trade credit and bargaining power and find a positive relationship (Klapper et. al. 2012; Murfin and Njoroge 2015; Breza and Liberman 2017; Giannetti et. al. 2021) However, with the exception of Giannetti et. al. (2021), all of these studies use firm level trade credit data, rather than customer-supplier pair level data, which limits the scope of the empirical studies.

The theory that I propose relates most closely to the two trade credit theories that con-

sider the interaction between trade credit and competition, Chod et. al. (2019) and Giannetti et. al. (2021). Chod et. al. (2019) build on the idea from the standard trade credit theory that giving trade credit to constrained customers helps them finance additional purchases. They consider that input market competition decreases supplier incentives give trade credit to constrained customers because trade credit helps customers finance additional purchases from rival suppliers. I apply this logic in reverse. That is, output market competition increases customer incentives to take trade credit from constrained suppliers because trade credit prevents suppliers from financing additional sales to rival customers.

Similar to Giannetti et. al. (2021), I also investigate the connection between trade credit and bargaining power. In their theory, suppliers use trade credit to preserve downstream competition, where taking trade credit raises large customer marginal costs of producing at high quantities and keeps small customers in the market. I consider that trade credit is at tool for large firms to influence competition, where trade credit raises supplier marginal costs of producing for rival customers. I show that the opposite result emerges upon assuming that contracts are decided sequentially, rather than simultaneously, and the supplier is at its outside option, rather than the large customer, is at its outside option. That is, I find that these two assumptions result in large customers using trade credit to decrease competition, rather than small suppliers using trade credit to increase competition.

3 Model

I consider an economy that consists of one supplier S selling to two competing retailers $R_{i \in \{1,2\}}$. Retailers differ in size, where R_1 is large and R_2 is small. The supplier produces intermediate inputs at constant marginal cost c of raw materials. Retailers purchase input quantities $\mathbf{q} = \{q_1, q_2\}$ from the supplier to produce differentiated final goods at no additional cost.

Equations (1) and (2) display the inverse demand functions for the final goods. The demand intercept represents size and is normalized to 1 for the small retailer and set to $z > 1$ for the large retailer. The parameter $\epsilon \in [0, 1]$ represents product substitutability and therefore the degree of competitive interaction among retailers. The demand intercept represents size and is normalized to 1 for the small retailer and set to $z > 1$ for the large retailer.

$$P_1(\mathbf{q}) = z - \epsilon q_2 - q_1 \tag{1}$$

$$P_2(\mathbf{q}) = 1 - \epsilon q_1 - q_2 \tag{2}$$

3.1 Timeline

There are two periods and three stages of decision making. All stages of decision making occur in period one. In stages one and two, the supplier bargains with retailers over a contract for the input purchase, where stage one is with R_1 and stage two is with R_2 . The contract between S and R_i is $\mathbf{x}_i^* = \{q_i, p_i, \tau_i\}$, where q_i is the order quantity, p_i is the price per unit, and τ_i is the share of the payment purchased with trade credit. In stage three, financing and production occur. Here, firms take out bank loans, b , retailers pay the supplier the share purchased with cash, and the supplier produces and sells the inputs.

In period two, retailers produce and sell the final good and pay the supplier the share purchased with trade credit. Firms repay their bank loans with interest. Firms discount cash flows at the same rate, and all cash flows are expressed in present value terms.

3.2 Profit functions

Each firm's profit is a function of the two equilibrium supply contracts and its own loan size. The profit function for S is

$$\pi_S(\mathbf{x}_1, \mathbf{x}_2, b_S) = p_1q_1 + p_2q_2 - c(q_1 + q_2) - r_S b_S \quad (3)$$

which consists of revenues, $p_1q_1 + p_2q_2$, less input costs $c(q_1 + q_2)$ and financing costs $r_S b_S$.

The profit function for R_i is

$$\pi_{R_i}(\mathbf{x}_1, \mathbf{x}_2, b_i) = P_i(\mathbf{q})q_i - p_iq_i - r_i b_i \quad (4)$$

which consists of revenues $P_i(\mathbf{q})q_i$ less input costs p_iq_i and financing costs $r_i b_i$.

3.3 Financing

Firms must finance any time gap between when input costs are paid and revenue is received. Retailers may use a combination of trade credit, and bank loans. Trade credit allows R_i to delay a share τ_i of the total payment from period 1 to period 2. This means that $1 - \tau_i$ of the sale is purchased with cash and paid in period 1, while τ_i of the sale is purchased with trade credit and paid in period 2.⁵In practice, late payments are widespread. Approximately 70% of observations in the dataset in this paper contain

⁵I assume the trade credit share is bounded by 0 and 1. In practice, this tends to be true, except in times of widespread financial crisis, such as in 2008. The theoretical basis for this assumption is that there are additional factors outside of the model that discourage pre-payment (τ below 0) or a loan in excess of the input purchase (τ above 1). On the below 0 side, when the customer has pre-paid, there is additional risk for customer in that the supplier might not deliver or might deliver late. On the above 1 side, when the supplier lends in excess of the input value, there is additional risk for the customer in that the excess lending is not backed by collateral.

overdue balances, with an average overdue share of 28%. Late payment is particularly relevant for the question in this paper as news articles frequently quote suppliers who complain about large customers paying well beyond official payment terms. For these reasons, I interpret τ_i as a combination of official payment terms and an expected delay beyond terms.

While I do not model late payment explicitly, there are a couple reasons why a significant portion of payment delays should be reflected in late payment. One is that it is common courtesy in business to business transactions for suppliers to allow an unofficial grace period without any deterioration in the business relationship or late payment penalties.⁶ Another is that extending official payment terms for one customer may strengthen the bargaining position of other customers as they may be able to argue that they deserve the same terms.⁷ I assume that expected late payment increases with official terms.

The supplier may use a combination of internal funds and bank loans, but not trade credit. One may imagine that the supplier could use trade credit to delay payment to its own suppliers from period zero to period 1. I don't allow suppliers to take trade credit because this introduces complexities both associated with introducing an entire chain of vertical production stages and with introducing the maturity dimension of bank loans. To eliminate a scenario where suppliers take trade credit, I make two assumptions. The first is that there is no delay between when the supplier purchases raw materials and sells its input—both occur in period one. The second is that firms may not delay payment to periods beyond when they sell their products.

External financing incurs a cost following Kaplan and Zingales (1995). I assume that the cost of bank credit is convex in the size of the loan without explicitly modeling its micro foundations. Specifically, the interest rate on bank credit increases linearly in the size of the loan. Accordingly, the interest rate that the bank charges the supplier is

$$r_S = \theta_S b_S \tag{5}$$

for a loan of size b_S , where $\theta_S \geq 0$ is a parameter that represents the severity of the supplier's external financing frictions and increases the cost of external financing. Retailer financing costs are symmetric. The interest rate that the bank charges the retailer i is

⁶Using 1996 survey data from the Credit Research Foundation, Wilner (2000) documents that although firms may require late fees and interest penalties for delinquent payment, these frequently are not enforced. On average, trade creditors start assessing late payment penalties after 18 days of delinquency and that less than half the amount of the assessed penalties are actually collected.

⁷Anecdotally, when news sources have asked customers why they delay payment to suppliers, the answer is sometimes that they want the same terms as their competitors. See for example New York Times article: "Big Companies Pay Later, Squeezing Their Suppliers". <https://www.nytimes.com/2015/04/07/business/big-companies-pay-later-squeezing-their-suppliers.html>

$$r_i = \theta_i b_i \quad (6)$$

for a loan of size b_i , where $\theta_i \geq 0$ is a parameter that represents the severity of retailer i 's external financing frictions and increases the cost of external financing.

In stage three, firms decide their loan sizes, taking each equilibrium contract \mathbf{x}_i^* from the prior stages as given. S 's equilibrium loan size $b_S^*(\mathbf{x}_1^*, \mathbf{x}_2^*)$ maximizes profits, subject to a financing constraint.

$$b_S^*(\mathbf{x}_1^*, \mathbf{x}_2^*) = \arg \max_{b_S \geq 0} \pi_S(\mathbf{x}_1^*, \mathbf{x}_2^*, b_S) \quad (7)$$

Subject to:

$$S \text{ financing constraint: } c(q_1^* + q_2^*) \leq (1 - \tau_1^*)p_1^*q_1^* + (1 - \tau_2^*)p_2^*q_2^* + b_S + w_S$$

The financing constraint states that the S must have enough funds (right side) to cover production costs (left side) due in period one. Period one production costs are the entire cost of raw materials. Available funds are the sum of internal and external funds. Internal funds consist of up front payment from its customers, $(1 - \tau_1^*)p_1^*q_1^* + (1 - \tau_2^*)p_2^*q_2^*$ and savings w_S , while external funds consist of borrowing b_S . I will focus on the case where $w_S = 0$. Note that trade credit enters into the financing constraint because it creates a gap between when production costs are incurred (period 1) and revenue is received (period 2). As a result, the supplier cannot finance period one production costs with revenue and must use savings or bank loans.

The necessary feature of the supplier's financing problem is that extending trade credit to one retailer makes it more difficult for the supplier to fund its relationships with other retailers. I model this difficulty as the supplier's ability to extend trade credit to other retailers because of its simplicity and testable predictions. However, this modeling choice is not meant to confine the narrative. If the supplier needs to pay its own suppliers in period zero, extending trade credit to one customer makes it more difficult to finance the time gap to produce other customer's inputs, even if those other customers take zero trade credit.

Similar to the supplier's strategy, R_i 's equilibrium loan size $b_i^*(\mathbf{x}_i^*)$ maximizes profits, subject to a financing constraint.

$$b_i^*(\mathbf{x}_1^*, \mathbf{x}_2^*) = \arg \max_{b_i \geq 0} \pi_{R_i}(\mathbf{x}_1^*, \mathbf{x}_2^*, b_i) \quad (8)$$

Subject to:

$$R_i \text{ financing constraint: } (1 - \tau_i^*)p_i^*q_i^* \leq b_i$$

The financing constraint states that the R_i must have enough funds (right side) to

cover the production costs (left side) due in period one. Period one production costs are the up-front payment to the supplier for intermediate inputs. Available funds are the sum of internal and external funds. Internal funds consist of savings w_S , while external funds consist of borrowing b_S .

3.4 Bargaining

Supply contracts are determined in bilateral bargaining.⁸ Negotiations occur sequentially via Nash bargaining in two stages. I assume that the supplier bargains with more important customers first, so stage one is between S and R_1 and stage two is between S and R_2 . The sequential assumption is not necessary as the bargaining game can be recast as a simultaneous move game in which the small firm is a collection of atomistic firms.

The contract between the S and R_i is $\mathbf{x}_i^* = \{q_i, p_i, \tau_i\}$, where q_i is the order quantity, p_i is the price per unit, and τ_i is the share of the payment purchased with trade credit.⁹

Before making simplifying assumptions, I make the bargaining framework clear by formulating the generalized Nash bargaining solution between S and R_i . The generalized Nash bargaining solution between S and R_i is the contract in equation 9

$$\mathbf{x}_i^* = \{q_i^*, p_i^*, \tau_i^*\} = \arg \max_{q_i, p_i, \tau_i \geq 0} (\pi_{R_i} - \pi_{R_i}^D)^{\gamma_i} (\pi_S - \pi_{S_i}^D)^{1-\gamma_i} \quad (9)$$

Subject to:

S participation constraint: $0 \leq \pi_S - \pi_{S_i}^D$

R_i participation constraint: $0 \leq \pi_{R_i} - \pi_{R_i}^D$

where the disagreement payoffs are denoted by $\pi_{S_i}^D$ and $\pi_{R_i}^D$. The parameter $\gamma_i \in [0, 1]$ reflects the asymmetry in the two firms' bargaining power not captured by the disagreement payoffs and determines R_i 's share of the gains from trade. I refer to γ_i

⁸Bargaining stands in contrast to the monopsonistic view of buyer power. In the standard monopsony model, the supply side of the market is perfectly competitive and is represented by an upwards sloping supply curve. A firm exercises buyer power by withholding demand, so as to reduce the price in the upstream market. Bargaining, however, arises when the supply side is *imperfectly* competitive. A firm exercises buyer power by *threatening* to withhold demand, but without actually doing so. The supplier's ability to cope with losing the a large amount of demand determines the size of the discount that an important buyer can negotiate. (Inderst and Wey 2007, Chen 2008)

⁹Sufficiently complex contracts are often used to avoid the complication of double marginalization. Double marginalization is a phenomenon where firms at different vertical stages in the same supply chain each charge a markup to their price. Double marginalization decreases total profits and increases deadweight loss in the supply chain. Sufficiently complex contracts, like nonlinear contracts or two part tariffs, have been shown to eliminate such issues. Nonlinear contracts are contracts in which firms agree on a menu of prices as a function of the quantity, rather than a constant price. After signing the contracts, the supplier chooses the quantity (ex. O'Brien and Shaffer (1997), Inderst and Wey (2007), Chen (2019)). There are many examples of nonlinear pricing that serve as evidence that these contracts exist in practice (Inderst and Wey 2007).

as retailer i 's share parameter, $\pi_{R_i}^D$ as retailer i 's outside option, and $\pi_{S_i}^D$ as the supplier's outside option with retailer i . The participation constraints state that there must be gains from trade from reaching an agreement. Each firm's payoff must be at least as high as its disagreement payoff in order to participate in the transaction.

I make a few simplifying assumptions so that the problem has a closed form solution. I assume that the small retailer has a share parameter of zero, $\gamma_2 = 0$, and that the large retailer has a share parameter of 1, $\gamma_1 = 1$. This means that the bargaining problem reduces to the large retailer making a take-it-or-leave-it offer to the supplier and the supplier making a take-it-or-leave-it offer to the small retailer. I also assume that the retailer outside options are zero, $\pi_{S_2}^D = \pi_{R_2}^D = 0$.

I use the generalized bargaining solution to formulate the solution to each stage, starting with stage two. In stage two, S bargains with R_2 , taking stage one's equilibrium contract \mathbf{x}_1^* as given. To emphasize this dependency, I write the stage two equilibrium contract as $\mathbf{x}_2^*(\mathbf{x}_1^*)$. The stage two bargaining solution is $\mathbf{x}_2^*(\mathbf{x}_1^*) = \{q_2^*(\mathbf{x}_1^*), p_2^*(\mathbf{x}_1^*), \tau_2^*(\mathbf{x}_1^*)\}$ that maximizes the S 's profits subject to the small retailer's participation constraint and anticipating stage three equilibrium outcomes.

$$\mathbf{x}_2^*(\mathbf{x}_1^*) = \{q_2^*(\mathbf{x}_1^*), p_2^*(\mathbf{x}_1^*), \tau_2^*(\mathbf{x}_1^*)\} = \arg \max_{q_2, p_2, \tau_2 \geq 0} \pi_S(\mathbf{x}_1^*, \mathbf{x}_2, b_S^*(\mathbf{x}_1^*, \mathbf{x}_2)) \quad (10)$$

Subject to:

$$R_2 \text{ participation constraint: } 0 \leq \pi_{R_2}(\mathbf{x}_2, b_2^*(\mathbf{x}_2))$$

The participation constraint states that the R_2 must make at least zero profits. Stage three enter into the bargaining problem in that the supplier anticipates how its contract impacts the equilibrium loan sizes. To reflect the fact that the supplier internalizes the effect of its contract on the stage three equilibrium, I write b_S^* and b_2^* as functions of \mathbf{x}_2 .

In stage one, the S bargains with R_1 . Because $\gamma_1 = 1$, the stage one problem reduces to the large retailer making a take-it-or-leave-it offer.¹⁰ I also assume that the large retailer's outside option is a constant. Without loss of generality, let the constant $\pi_{R_1}^D = 0$.

The supplier's outside option is the profits that it would receive from forgoing the sale to R_1 and only selling to R_2 . In this case, the stage two contract would adjust for the fact that the supplier no longer transacts with R_1 . Similarly, the stage three loan sizes would also adjust. Accordingly, the supplier's outside option is its equilibrium profits evaluated at $x_1^* = 0$

$$\pi_{S_1}^D = \pi_S^*(\mathbf{0}, \mathbf{x}_2^D, b_S^D) = p_2^D q_2^D - c q_2^D - r_S^D b_S^D \quad (11)$$

where \mathbf{x}_2^D is the stage two equilibrium contract evaluated at $\mathbf{x}_1^* = \mathbf{0}$, b_S^D is the supplier's

¹⁰The IO literature contains micro foundations and evidence to support the claim that large firms should have high bargaining power parameters.

equilibrium loan size evaluated at $\mathbf{x}_1^* = \mathbf{0}$ and $\mathbf{x}_2^* = \mathbf{x}_2^D$, and r_S^D is the corresponding interest rate.

With these assumptions in hand, the stage one bargaining solution is the contract $\mathbf{x}_1^* = \{q_1^*, p_1^*, \tau_1^*\}$ that maximizes R_1 's profits, subject to the supplier's participation constraint and anticipating both the stage two and three equilibrium outcomes.

$$\mathbf{x}_1^* = \{q_1^*, p_1^*, \tau_1^*\} = \arg \max_{q_1, p_1, \tau_1 \geq 0} \pi_{R_1}(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1), b_1^*(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1))) \quad (12)$$

Subject to:

$$S \text{ participation constraint: } 0 \leq \pi_S(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1), b_S^*(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1))) - \pi_{S_1}^D$$

The participation constraint states that the supplier's profits must be greater than or equal to the profits it would earn from only selling to R_2 .

Stage two enters into the bargaining problem in that R_1 anticipates how its contract impacts the equilibrium contract between the S and R_2 . To reflect the fact that the R_1 internalizes the effect of its contract on stage two equilibrium, I write \mathbf{x}_2^* as a function of \mathbf{x}_1 . Similar to stage two, stage three enters into the bargaining problem in that the R_1 anticipates how its contract impacts the equilibrium loan sizes. To reflect the fact that R_1 internalizes the effect of its contract on the stage three equilibrium, I write b_1^* and b_S^* as functions of \mathbf{x}_1 .

4 Equilibrium

The equilibrium is the set $\{\mathbf{x}_1^*, \mathbf{x}_2^*, b_S^*, b_1^*, b_2^*\}$ given by equations 7, 8, 10, and 12. I solve the model by backwards induction. Since the focus of the paper is explaining trade credit patterns, I focus on the determinants of equilibrium trade credit. To determine the key trade-offs involved in R_1 and R_2 's trade credit taking, I make use of the first order conditions on τ_1 and τ_2 .

Equation 13 shows the first order condition on τ_2 . This equation comes from the optimization problem described in equation 10, which takes \mathbf{x}_1^* as given and chooses $\mathbf{x}_2 = \{q_2, p_2, \tau_2\}$ to maximize S 's profits subject to R_2 's participation constraint and anticipating b_S and b_2 in the subsequent stage. Please see model appendix for proof.

Note that b_S^* and b_2^* depend on τ_2 , while the other equilibrium objects are not. For notational simplicity, Equation 13 suppresses these dependencies. For example, $b_S^*(\tau_2)$ is written as b_S^* and one would use the chain rule to expand this partial derivative. The reason why these dependencies are as such is due to the sequential bargaining setup. The large retailer's supply contract is chosen in stage 1, before the small retailer's contract, so \mathbf{x}_1^* is therefore taken as given in the τ_2 decision. Similarly, q_2 and p_2 are chosen in stage 2, in conjunction with τ_2 . Because they are chosen simultaneously, they

are therefore taken as given in the τ_2 decision. However, b_S and b_2 are chosen in stage 3, so are therefore functions of all prior equilibrium objects (i.e. \mathbf{x}_1^* and \mathbf{x}_2^*). Accordingly, they depend on τ_2 .

$$\underbrace{\frac{\partial r_S^* b_S^*}{\partial \tau_2}}_{\text{Marginal cost}} = \underbrace{\frac{\partial r_2^* b_2^*}{\partial \tau_2}}_{\text{Marginal benefit}} \quad (13)$$

Because the supplier has a share parameter of 1 with R_2 , the supply contract is in the supplier's hands. The supplier's marginal cost of trade credit is the increase in its own financing costs, $\frac{\partial r_S b_S}{\partial \tau_2}$. The supplier's marginal benefit of trade credit is the effect of trade credit in relaxing R_2 's participation constraint. This is the effect of alleviating R_2 's financial constraint in stage 3 and is equal to the effect of trade credit on the small retailer's savings on financing costs, $\frac{\partial r_2 b_2}{\partial \tau_2}$.

Equation 14 shows the first order condition on τ_1 , which shows R_1 trade credit incentives. This equation comes from the optimization problem described in equation 12, which chooses $\mathbf{x}_1 = \{q_1, p_1, \tau_1\}$ to maximize R_1 's profits subject to S 's participation constraint and anticipating how components of its contract will affect the equilibrium values \mathbf{x}_2^* , b_S^* , b_1^* , and b_2^* in the subsequent stages. Please see model appendix for proof.

Note that \mathbf{x}_2^* , b_S^* , b_1^* and b_2^* depend on τ_1 , while the other equilibrium objects do not. For notational simplicity, Equation 14 suppresses these dependencies. For example, the function $q_2^*(q_1^*, p_1^*, \tau_1)$ is written as q_2^* . The reason why these dependences are as such is due to the sequential bargaining setup. Since q_1 and p_1 are chosen in stage 1, in conjunction with τ_1 , they are taken as given in the τ_1 decision. However, since \mathbf{x}_2^* , b_S^* , b_1^* and b_2^* are chosen in stages 2 and 3, they are functions of the prior equilibrium object, \mathbf{x}_1^* . Accordingly, they are functions of τ_1 .

$$\underbrace{\frac{\partial r_S^* b_S^*}{\partial \tau_1} + \frac{\partial r_2^* b_2^*}{\partial \tau_1} - \frac{\partial (P_2^* - c) q_2^*}{\partial \tau_1}}_{\text{Marginal cost}} = \underbrace{-\frac{\partial r_1^* b_1^*}{\partial \tau_1} + \frac{\partial P_1^* q_1^*}{\partial \tau_1}}_{\text{Marginal benefit}} \quad (14)$$

R_1 's marginal cost is effect of trade credit on the supplier's profits. In order to keep the supplier at its outside option, the large retailer has to compensate the supplier for the full value of these costs, otherwise the supplier will sell solely through the small retailer. R_1 's marginal benefit is the effect of trade credit on revenues $\frac{\partial P_1^* q_1^*}{\partial \tau_1}$ and financing costs $\frac{\partial r_1^* b_1^*}{\partial \tau_1}$. R_1 chooses the trade credit value that equates marginal cost with marginal benefit.

Before explaining these conditions in more detail, I consider several benchmark models, where I remove the key features of the full model. The purpose of this is to highlight the key departures from traditional trade credit theory and understand why they are able to explain the empirical patterns.

4.1 Frictionless benchmark

Since a strategic product market interaction is at the heart of the theory, I start by removing competition by removing one retailer and analyzing bilateral decisions. Equations 15 and 16 display the first order conditions on τ_2 and τ_1 when the other retailer does not exist. Although equation 15 looks identical to equation 13, the difference is that b_S and b_2 are functions of ϵ in equation 13, but not equation 15.

$$\underbrace{\frac{\partial r_S^* b_S^*}{\partial \tau_2}}_{\text{Marginal cost}} = - \underbrace{\frac{\partial r_2^* b_2^*}{\partial \tau_2}}_{\text{Marginal benefit}} \quad (15)$$

$$\underbrace{\frac{\partial r_S^* b_S^*}{\partial \tau_1}}_{\text{Marginal cost}} = - \underbrace{\frac{\partial r_1^* b_1^*}{\partial \tau_1}}_{\text{Marginal benefit}} \quad (16)$$

In the frictionless benchmark, firms do not face financial constraints. I define an unconstrained firm as one with enough savings to cover its production costs in full. I represent an unconstrained firm in the model with the assumption that the firm faces no financial frictions, $\theta = 0$. When firms do not face financial constraints, their financing costs are 0 and therefore do not depend on trade credit. We can see this independence reflected in equations 15 and 16 as both the marginal cost and benefits of the retailer first order conditions on trade credit are 0. This means that any trade credit value will satisfy the first order conditions, and the equilibrium trade credit variables, τ_1^* and τ_2^* , span the entire choice sets. In other words, firms are indifferent towards trade credit in this case.

4.2 Standard benchmark

In the standard benchmark, I allow the supplier to face financial constraints, $\theta_S > 0$. This corresponds with the traditional trade credit theory.

I consider that the supplier is constrained, but the retailers are unconstrained. For the τ_2 decision, the supplier doesn't benefit from extending trade credit, but incurs a cost. There is no benefit because R_2 doesn't face any financial constraints that trade credit would help alleviate. Accordingly, the supplier can't charge a higher price in exchange for extending trade credit. On the cost side, because the supplier is constrained, extending trade credit forces the supplier to borrow more and pay higher financing costs in order to fund its production costs. In terms of equation 15, this means that the marginal benefit of trade credit is 0, while the marginal cost of trade credit is strictly increasing and intersects the marginal benefit at $\tau_2 = 0$. Accordingly, when R_2 is unconstrained, the equilibrium trade credit is 0.

The τ_1 decision mirrors the τ_2 decision. R_1 doesn't benefit from taking trade credit, but incurs a cost. There is no benefit because R_1 doesn't face any financial constraints

for trade credit to alleviate. On the cost side, because the supplier is constrained, taking trade credit forces the supplier to borrow more and pay higher financing costs in order to fund its production costs. R_1 has to compensate the supplier for these additional financing costs so that the supplier remains at its outside option. In terms of equation 16, this means that the marginal benefit of trade credit is 0, while the marginal cost of trade credit is strictly increasing and intersects the marginal benefit at $\tau_1 = 0$. Accordingly, when R_1 is unconstrained, the equilibrium trade credit is 0.

These standard benchmark predictions are that of the traditional trade credit theory. In the standard benchmark, the model predicts that an unconstrained retailer should take zero trade credit from a constrained supplier. The fact that unconstrained firms take lots of trade credit from constrained suppliers is at odds with the traditional theory and is what this theory attempts to explain.

4.3 Two retailers

In this section, I show conditions under which an unconstrained customer will trade credit from a constrained supplier and explain the factors that determine how much.

In both sections 4.2 and 4.3, I look at an unconstrained retailer's decision to take trade credit from a constrained supplier. This means looking at R_1 's trade credit decision assuming R_1 is unconstrained and R_2 's trade credit decision assuming R_2 is unconstrained. The difference between section 4.2 and section 4.3 is in section 4.3 there are two competing retailers. When retailers compete it's possible that the competing retailer faces financial constraints. Accordingly, for R_1 's trade credit decision in section 4.3, I assume that R_1 is unconstrained, but make no assumptions on R_2 's constraints. Similarly, for R_2 's trade credit decision in section 4.3, I assume that R_2 is unconstrained, but make no assumptions on R_1 's constraints.

I start with R_2 . Because R_2 's trade-off does not change, an unconstrained R_2 still takes zero trade credit. As such, the first necessary condition is that the retailer must be R_1 . In other words, the retailer must be large enough relative to the supplier's other customers in order to take sequential priority in bargaining.

Now I focus on R_1 and consider the τ_1 decision when R_1 is unconstrained and the supplier is constrained. When R_1 is unconstrained, $\frac{\partial r_1^* b_1^*}{\partial \tau_1} = 0$. Accordingly, the first order condition on τ_1 becomes

$$\underbrace{\frac{\partial r_S^* b_S^*}{\partial \tau_1} + \frac{\partial r_2^* b_2^*}{\partial \tau_1} - \left(\frac{\partial (P_2^* - c) q_2^*}{\partial \tau_1} \right)}_{\text{Marginal cost}} = \underbrace{\frac{\partial P_1^* q_1^*}{\partial \tau_1}}_{\text{Marginal benefit}} \quad (17)$$

Equation 18 simplifies equation 17 as much as possible. It stops short of plugging in the solutions for the equilibrium variables in terms of the exogenous parameters because the equation becomes too algebraically complex.

$$\begin{aligned}
\underbrace{\frac{2}{c}(b_S^* + b_2^*) \frac{\partial q_2^*}{\partial \tau_1}}_{\text{Financing costs}} + \underbrace{(P_2^* - q_2^* - c) \frac{\partial q_2^*}{\partial \tau_1}}_{\text{Output effect}} = \underbrace{\epsilon q_1^* \frac{\partial q_2^*}{\partial \tau_1}}_{\text{Competition effect}} \quad (18) \\
\text{Marginal cost} \qquad \qquad \qquad \text{Marginal benefit}
\end{aligned}$$

R_1 's marginal cost is effect of trade credit on the supplier's profits. In order to keep the supplier at its outside option, the large retailer has to compensate the supplier for the full value of these costs, otherwise the supplier will sell solely through the small retailer. The first term is a composite of direct and indirect financing costs. The direct financing costs come from how τ_1 increases the supplier's financing costs. Trade credit forces the supplier to borrow more in order purchase inputs, which directly increases the supplier's borrowing costs. The indirect financing costs come from how τ_1 increases R_2 's financing costs. Because the supplier now needs to borrow at a higher rate in order to offer trade credit to R_2 , the supplier optimally offers less trade credit to R_2 . This forces R_2 to borrow more and increases R_2 's financing costs. Consequently, the supplier needs to lower the price it charges R_2 in order for R_2 to remain at its outside option. The second term is an output effect. Here, the increased borrowing required to sell to R_2 constitute higher marginal costs and result in a lower optimal quantity sold.

R_1 's marginal benefit is the effect of trade credit on revenues. This is a competition effect stemming from R_2 's output decrease. Because retailers sell competing products, this increases R_1 's output price, which increases R_1 's profits. In equilibrium, R_1 chooses the τ_1 that equates the marginal cost of keeping the supplier at its outside option—compensation for higher financing costs and being unable to sell as much to R_2 —with the marginal benefit of higher prices due to R_2 's quantity decrease.

Using equation 18, I show the second necessary condition for an unconstrained retailer to take positive trade credit. This is $\epsilon > 0$, meaning that the two retailers' products are substitutes. To see this, consider that $\epsilon \leq 0$, meaning that the two retailer's products are either unrelated (equality case) or complements (inequality case). Examining equation 18, $\epsilon \leq 0$ makes the marginal benefit side of the equation (right side) less than or equal to 0, but does not affect the marginal cost side (left side), which remains strictly above 0. This means that the marginal cost of trade credit is higher than the marginal benefit of trade credit for any level of positive trade credit. In other words, the benefits of trade credit never justify the costs, leaving $\tau_1^* = 0$. This argument shows that $\epsilon \leq 0$ implies $\tau_1^* = 0$, allowing us to conclude that $\epsilon > 0$ is necessary for $\tau_1^* > 0$.

The condition that is both necessary and sufficient for $\tau_1^* > 0$ equates the marginal cost (left) side of equation 18 with the marginal benefit (right) side of equation 18 when $\tau_1 = 0$. This condition is a function of the other exogenous parameters, θ_S , θ_2 , ϵ , z , and c , but the exact formula is too algebraically complex to provide any additional insight. Changing each of these exogenous parameters shifts the marginal cost and/or benefit of τ_1 and will decide whether or not an unconstrained R_1 will choose $\tau_1^* > 0$ as well as how

much trade credit R_1 will choose.

Lastly, I show conditions under which τ_1^* is unique. I show uniqueness in two steps. First, I show that τ_1^* does not span the entire choice set, which would render R_1 indifferent towards trade credit. The two conditions are that both the supplier and R_2 must face financial frictions. To see this, assume that either θ_S or θ_2 equals 0. Equation 19 displays the formula for $\frac{dq_2^*}{d\tau_1}$ and shows that $\frac{dq_2^*}{d\tau_1} = 0$ in either case.

$$\frac{\partial q_2^*}{\partial \tau_1} = -c \cdot \frac{\theta_S \theta_2 \rho_1^* q_1^*}{c^2 \theta_S \theta_2 + \theta_S + \theta_2} \quad (19)$$

When $\frac{\partial q_2^*}{\partial \tau_1} = 0$, both the marginal cost and benefit sides of the equation 18 equal to 0 no matter the value of τ_1 . Since any τ_1 will satisfy the first order condition, R_1 is indifferent towards trade credit.

Intuitively, if $\theta_S = 0$, then the supplier faces no financing costs and will extend as much trade credit to the small retailer as necessary to fund the purchase. This means that there will be no financing costs associated with producing for the small retailer and the large retailer's trade credit won't change the small retailer's quantity. If $\theta_2 = 0$, then the small retailer faces no financing costs and will pay as early as necessary so that the supplier won't need to pay any extra financing costs in order to fund production for the small retailer. This means that there will be no financing costs associated with producing for the small retailer and the large retailer's trade credit won't change the small retailer's quantity.

Second, assuming these conditions, I show that the marginal cost and benefit of trade credit intersect at a unique point. This is because the marginal benefit is constant in τ_1 and marginal cost is strictly increasing in τ_1 . Figure 1 shows this visually. The constant marginal benefit is due to the fact that the terms of the \mathbf{x}_1 contract are chosen simultaneously, so the equilibrium condition on τ_1 takes q_1^* as a constant. The strictly increasing marginal cost is due to the fact that b_S^* and b_2^* are strictly increasing in τ_1 , q_2^* is strictly decreasing in τ_1 , and c is constant in τ_1 . See model appendix for details.

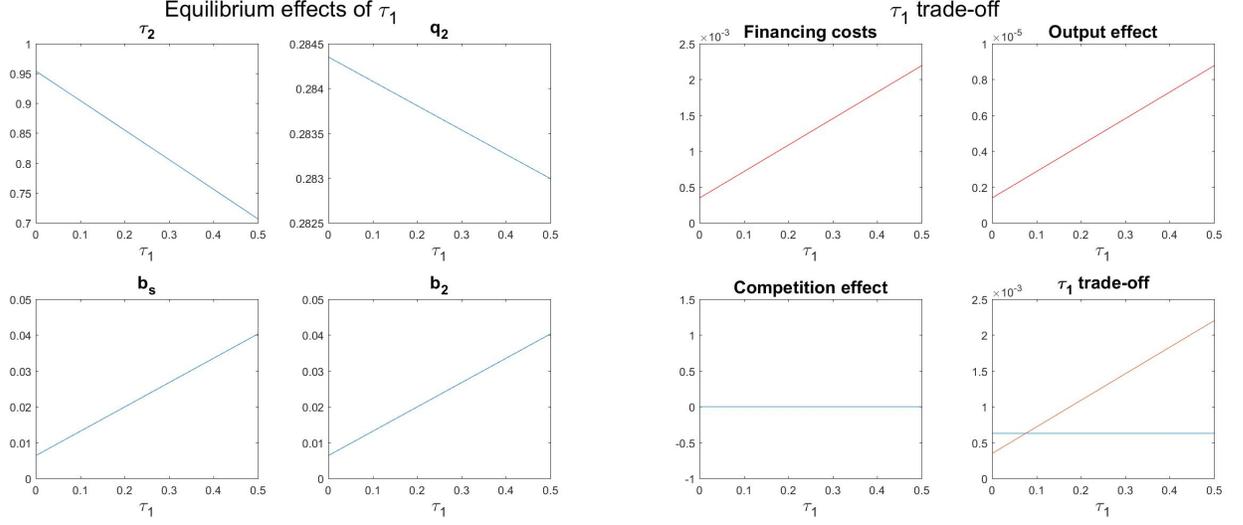


Figure 1: This figure displays R_1 's trade-off in choosing τ_1 when R_1 does not face financial frictions. The left group of charts show how τ_1 affects the equilibrium variables in subsequent stages. The right group of charts shows the terms that comprise the marginal benefit and marginal cost of τ_1 .

4.4 Full model

In this section I allow both retailers to face financial constraints. I show the conditions that pin down equilibrium trade credit in the full model and explain the factors that determine the marginal cost and benefit of taking trade credit for each retailer.

First, I focus on R_1 's trade credit. Equation 20 shows the first order condition on τ_1 , where the only change from equation 18 is that R_1 faces financial frictions. This change results in an additional marginal benefit term, $-\frac{\partial r_1^* b_1^*}{\partial \tau_1} = 2\theta_1 b_1^* p_1^* q_1^*$, which captures the amount that R_1 saves on external financing costs by taking trade credit.

$$\underbrace{\frac{2}{c}(b_s^* + b_2^*) \frac{-\partial q_2^*}{\partial \tau_1} + (P_2^* - q_2^* - c) \frac{-\partial q_2^*}{\partial \tau_1}}_{\text{Marginal cost}} = \underbrace{\underbrace{2\theta_1 b_1^* p_1^* q_1^*}_{\text{Financing savings}} + \underbrace{\epsilon q_1^* \frac{-\partial q_2^*}{\partial \tau_1}}_{\text{Competition effect}}}_{\text{Marginal benefit}} \quad (20)$$

Figure 2 reproduces the plots in Figure 1 when R_1 faces financial constraints. The main difference is the additional marginal benefit term, financing savings. Since b_1 is decreasing in τ_1 , the marginal financing savings term, $2\theta_1 b_1^* p_1^* q_1^*$, is decreasing in τ_1 . As a result, relative to the unconstrained R_1 case, the marginal benefit of τ_1 is decreasing instead of constant.

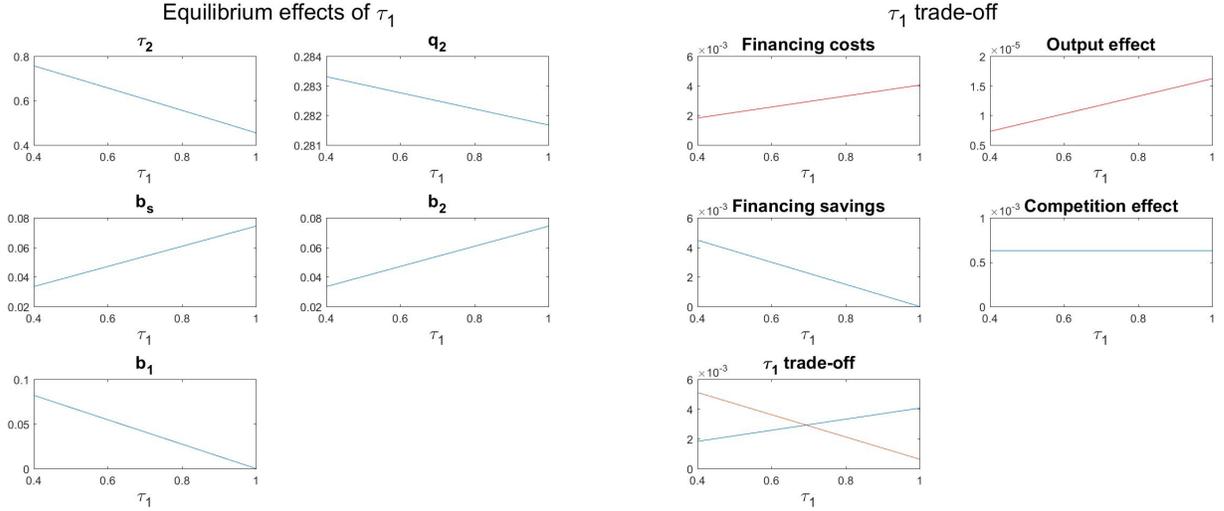


Figure 2: This figure displays R_1 's trade-off in choosing τ_1 when R_1 faces financial frictions. The left group of charts show how τ_1 affects the equilibrium variables in subsequent stages. The right group of charts shows the components of the marginal benefit and marginal cost of τ_1 as functions of τ_1 . The bottom chart shows the total marginal cost and total marginal benefit as functions of τ_1 , where the intersection represents the equilibrium τ_1^* .

Next, I turn to R_2 's trade credit. Equation 20 simplifies equation 13 and shows the first order condition on τ_2 .

$$\underbrace{\theta_S b_S^*}_{\text{Marginal cost}} = \underbrace{\theta_2 b_2^*}_{\text{Marginal benefit}} \quad (21)$$

The equation shows that the supplier extends trade credit to R_2 up to the point where the marginal increase in the supplier's financing costs equals the marginal decrease in R_2 's financing costs. Figure 3 shows this visually and will be used for reference in the next section in order to conduct comparative statics

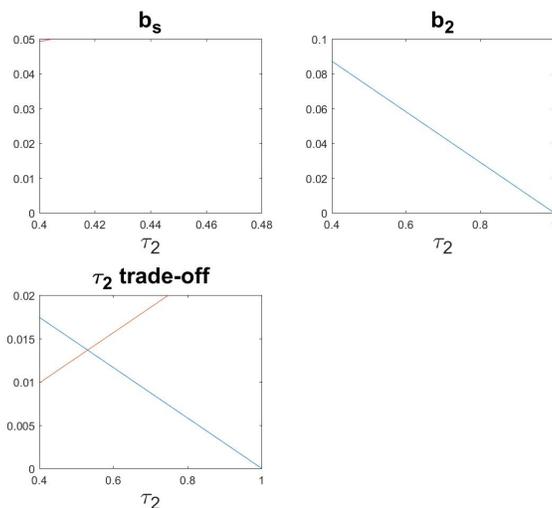


Figure 3: This figure displays the supplier's trade-off in choosing τ_2 when R_2 faces financial frictions. The top row shows how τ_2 affects the equilibrium variables in subsequent stages. The bottom chart shows the marginal cost and marginal benefit as functions of τ_2 , where the intersection represents the equilibrium τ_2^* .

5 Comparative statics and testable predictions

In this section, I conduct comparative statics and develop a set of testable predictions. I confine the analysis to the parameter combinations that guarantee a unique interior solution. I focus on the effects of exogenous parameters on equilibrium trade credit and use these relationships to define a set of testable predictions. The table below displays the baseline set of parameters that I use to produce the the plots in this section. I choose these specific values because they result in a unique interior solution.

Parameter	Value
θ_S	.2
θ_1	.2
θ_2	.2
c	.2
z	1.3
ϵ	0.5
w_S	0

Prediction 1: The supplier relative to customer financial frictions should have a negative effect on trade credit.

Note that this is the main prediction of the traditional trade credit theory. This means that these predictions are not useful in distinguishing my theory from traditional trade credit theories. However, they are still useful to test in the sense that these relationships should still hold after controlling for other features of the theory.

The comparative statics of interest for the first part of this statement are the effects of θ_S on τ_1^* and τ_2^* . The first row of figure 4 shows that as θ_S increases, both τ_1^* and τ_2^* decrease. In other words, as the supplier's financial frictions increase, customers take less trade credit.

The reason why τ_2^* decreases is because the supplier's cost of extending trade credit increases. We see this reflected in the supplier and small retailer's equilibrium loan sizes, where the supplier's loan size decreases and the small retailer's loan size increases. The reason why τ_1^* decreases is that it raises the large customer's marginal cost of trade credit. This happens because the large customer now needs to compensate the supplier more for its extra financing costs in order to still satisfy the supplier's outside option.

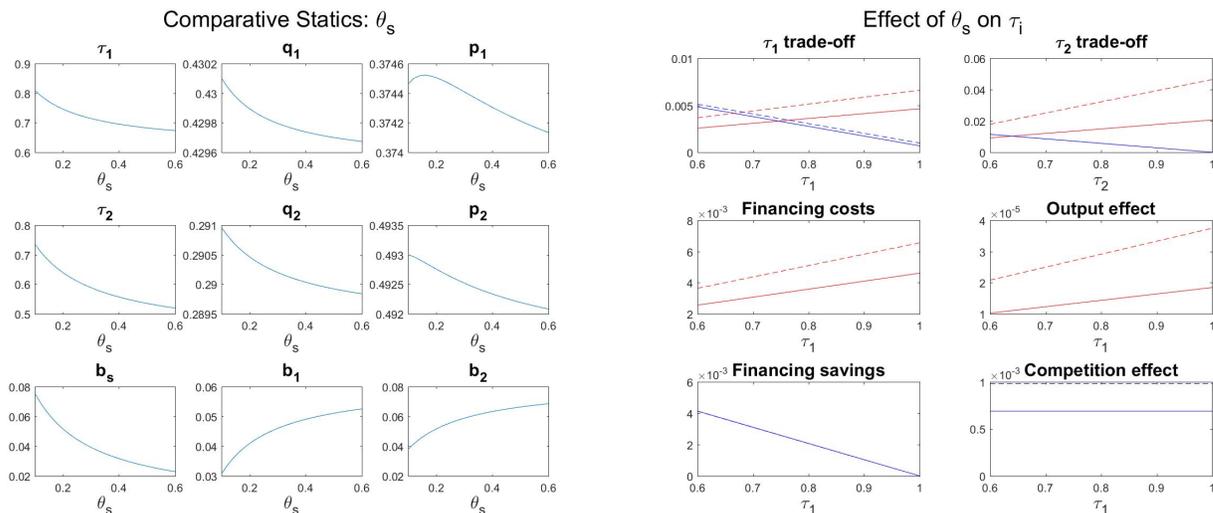


Figure 4: The left group of plots examines how θ_S affects the equilibrium. The x-axis represents different values of θ_S and y-axis represents the equilibrium variable of interest. The right group of plots examines how θ_S changes the trade-offs that determine equilibrium trade credit. Dashed lines represent an increase in θ_S . The top row displays the marginal cost and benefit of taking trade credit, where the left shows τ_1 and right shows τ_2 . Red lines represent the marginal cost and blue lines represent the marginal benefit. The middle row decomposes the marginal cost of τ_1 into financing costs and an output effect. The bottom row decomposes the marginal benefit of τ_1 into financing savings and a competition effect.

The comparative statics of interest for the second part of this statement are the effects of θ_1 on τ_1^* and θ_2 on τ_2^* . Figure 5 displays comparative statics for θ_1 , where the top left panel contains the effect of θ_1 on τ_1^* . Figure 6 displays comparative statics for θ_1 , where the top right panel contains the effect of θ_2 on τ_2^* . Both effects are straightforward. An increase in the R_1 's financial frictions increases its marginal benefit of taking trade credit.

Similarly, an increase in R_2 's financial frictions increases the supplier's marginal benefit of extending trade credit to R_2 .

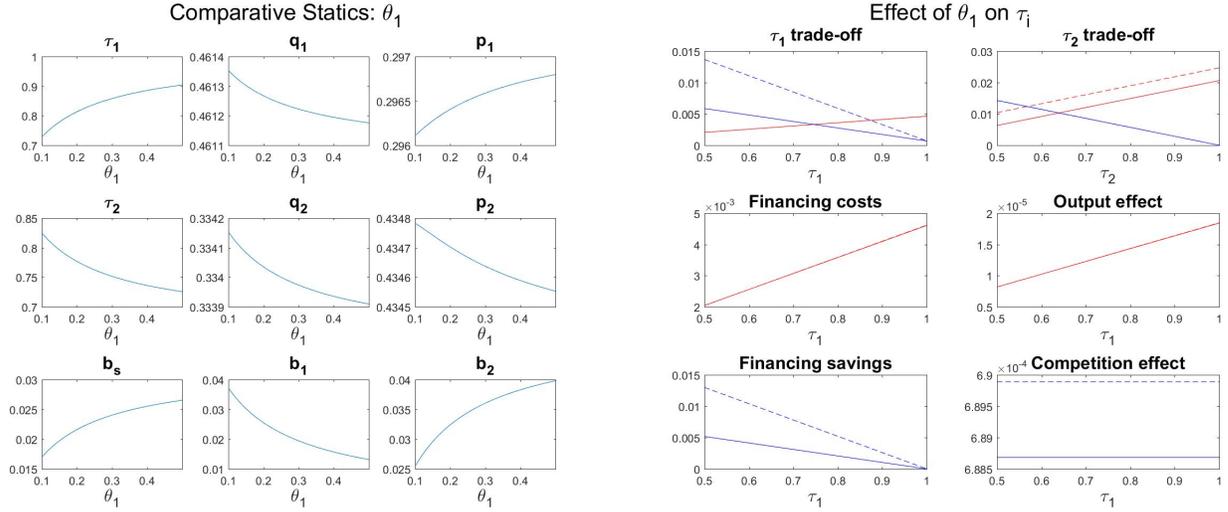


Figure 5: The left group of plots examines how θ_1 affects the equilibrium. The x-axis represents different values of θ_1 and y-axis represents the equilibrium variable of interest. The right group of plots examines how θ_1 changes the trade-offs that determine equilibrium trade credit. Dashed lines represent an increase in θ_1 . The top row displays the marginal cost and benefit of taking trade credit, where the left shows τ_1 and right shows τ_2 . Red lines represent the marginal cost and blue lines represent the marginal benefit. The middle row decomposes the marginal cost of τ_1 into financing costs and an output effect. The bottom row decomposes the marginal benefit of τ_1 into financing savings and a competition effect.

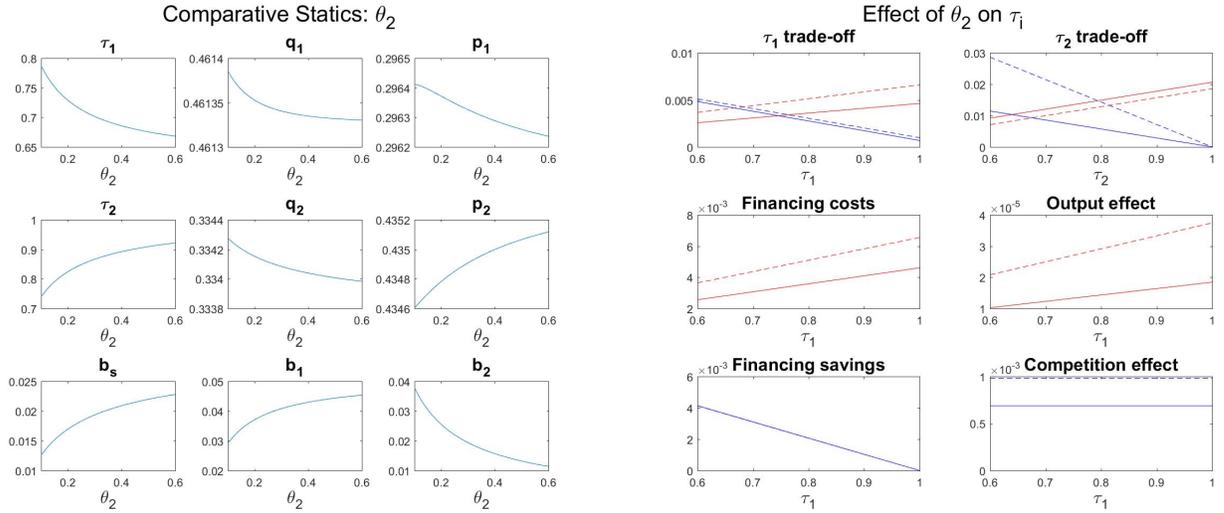


Figure 6: The left group of plots examines how θ_2 affects the equilibrium. The x-axis represents different values of θ_2 and y-axis represents the equilibrium variable of interest. The right group of plots examines how θ_2 changes the trade-offs that determine equilibrium trade credit. Dashed lines represent an increase in θ_2 . The top row displays the marginal cost and benefit of taking trade credit, where the left shows τ_1 and right shows τ_2 . Red lines represent the marginal cost and blue lines represent the marginal benefit. The middle row decomposes the marginal cost of τ_1 into financing costs and an output effect. The bottom row decomposes the marginal benefit of τ_1 into financing savings and a competition effect.

Prediction 2: The financial frictions of the supplier's other customers should have a negative effect on trade credit.

Prediction 2 make claims about how R_1 's trade credit should react to R_2 's financial frictions and vice versa. This means that the comparative static of interest for R_2 is the effect of θ_1 on τ_2^* . Similarly, the comparative static of interest for R_1 is the effect of θ_2 on τ_1^* . Figure 5 shows that the effect of θ_1 on τ_2^* is negative. When θ_1 is high, R_1 takes more trade credit. As a result, the supplier's marginal cost of extending trade credit to R_2 increases and τ_2^* decreases. Figure 6 also shows that the effect of θ_2 on τ_1^* is also negative. When θ_2 is high, the marginal cost of R_1 taking trade credit increases due to the financing cost channel. When θ_2 is high, extending trade credit to R_1 has a more negative effect on the profits that the supplier receives from producing for R_2 .

Prediction 3:

(a) Within the set of unconstrained customers, bargaining power should have a positive effect on trade credit.

(b) Within the set of high bargaining power customers, the customer's size should have a positive effect on trade credit.

Predictions 3a and 3b are about the relationship between size and trade credit. Prediction 3a is the first necessary condition for an unconstrained retailer to take trade credit. In terms of the model, this is the condition that the retailer must be R_1 .

Prediction 3b comments on the relationship between size and trade credit, but is different from bargaining power. This prediction identifies the effect of the customer's market size given that the customer has bargaining power. In terms of the model, this stems from comparative statics on z , the customer's market size. The comparative statics plots in Figure 7 show that as z increases, τ_1^* increases and τ_2^* decreases.

The main reason for the positive effect on τ_1^* is that z raises the marginal benefit of taking trade credit. Trade credit reduces the small retailer's quantity, which increases demand for the large retailer's product and, accordingly, the price that the large retailer receives. This price increase has a larger impact on the large retailer's revenue when the large retailer is producing at a higher quantity. The main reason for the negative effect on τ_2^* is that the supplier reacts to the higher τ_1^* . Extending trade credit to the large retailer raises the marginal cost of extending trade credit to the small retailer.

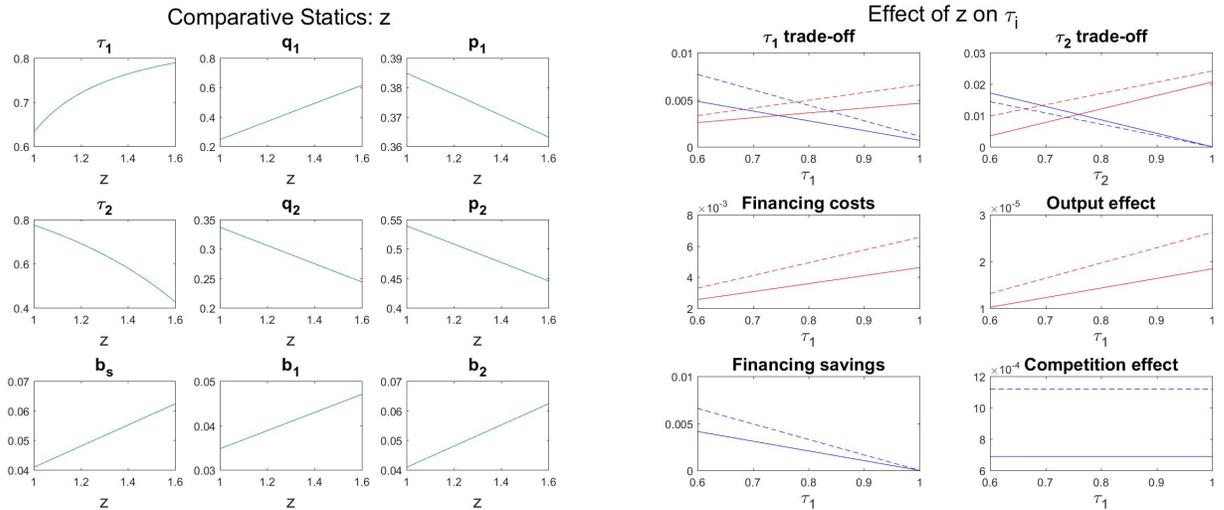


Figure 7: The left group of plots examines how z affects the equilibrium. The x-axis represents different values of z and y-axis represents the equilibrium variable of interest. The right group of plots examines how z changes the trade-offs that determine equilibrium trade credit. Dashed lines represent an increase in z . The top row displays the marginal cost and benefit of taking trade credit, where the left shows τ_1 and right shows τ_2 . Red lines represent the marginal cost and blue lines represent the marginal benefit. The middle row decomposes the marginal cost of τ_1 into financing costs and an output effect. The bottom row decomposes the marginal benefit of τ_1 into financing savings and a competition effect.

Prediction 4:

(a) For high bargaining power customers, product substitutability should have a positive effect on trade credit. For low bargaining power customers, product substitutability

should have a negative effect on trade credit. As an implication, product substitutability should have a more positive effect on trade credit when bargaining power is high compared to when bargaining power is low.

(b) The customer’s bargaining power should have a more positive effect on trade credit when product substitutability is high compared to when product substitutability is low..

These predictions stem from the comparative statics on ϵ , specifically the impact of ϵ on τ_1^* and τ_2^* . To address prediction 3a, the top left panel of the comparative statics plots in Figure 8 shows that the impact of ϵ on τ_1^* is positive. This is because the large customer’s marginal benefit of taking trade credit increases when it competes more closely with the supplier’s other customers. The top right panel of Figure 8 impact of ϵ on τ_2^* is negative. On the cost side, this is because the increase in τ_1^* forces the supplier to borrow, raising the supplier’s marginal cost of providing trade credit to the small retailer. This makes it more expensive for the supplier to fund production for the small retailer. On the benefit side, increasing ϵ shifts the demand curve inwards and incentives firms to reduce quantity. The quantity reduction lowers the small retailer’s financing needs, which lowers the marginal benefit of extending trade credit to the small retailer.

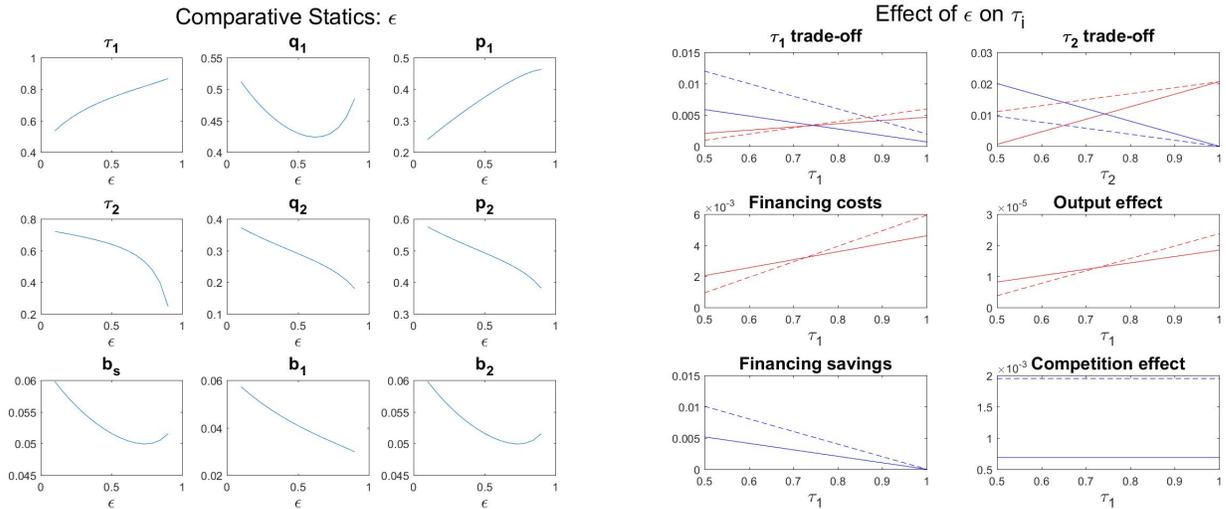


Figure 8: The left group of plots examines how ϵ affects the equilibrium. The x-axis represents different values of ϵ and y-axis represents the equilibrium variable of interest. The right group of plots examines how ϵ changes the trade-offs that determine equilibrium trade credit. Dashed lines represent an increase in ϵ . The top row displays the marginal cost and benefit of taking trade credit, where the left shows τ_1 and right shows τ_2 . Red lines represent the marginal cost and blue lines represent the marginal benefit. The middle row decomposes the marginal cost of τ_1 into financing costs and an output effect. The bottom row decomposes the marginal benefit of τ_1 into financing savings and a competition effect.

To address prediction 4b, Figure 9 plots τ_1^* and τ_2^* over the values of ϵ . By comparing the τ_1^* line (blue) with the τ_2^* line (red), the figure shows the effect of bargaining power. When product substitutability is low, the τ_1^* line is below τ_2^* line, revealing a negative

effect of bargaining power on trade credit. When product substitutability is high, the τ_1^* line is above τ_2^* line, revealing a positive effect of bargaining power on trade credit. Since the signs on these effects depend on the specific parameter values, I test the relative effect instead of testing the signs. Specifically, bargaining power should have a more positive effect on trade credit when product substitutability is high compared to when product substitutability is low.

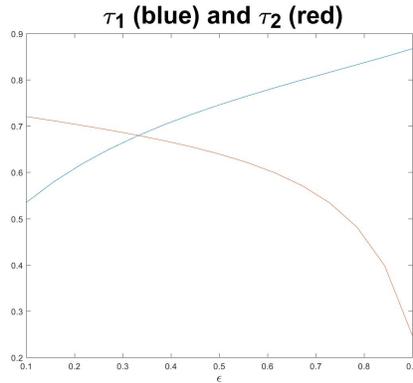


Figure 9: This figure examines how bargaining power affects trade credit over different levels of product substitutability. The y-axis contains trade credit, where the blue line represents τ_1 and red line represents τ_2 . The x-axis contains product substitutability.

Prediction 5:

- (a) Trade credit should increase in the supplier’s internal funds.
- (b) The supplier’s internal funds should have a more positive effect on trade credit when the supplier’s financial frictions are high and the customers’ financial frictions are low.
- (c) For high bargaining power customers, the supplier’s internal funds should have a more positive effect on trade credit when competition is low. For low bargaining power customers, the supplier’s internal funds should have a more positive effect on trade credit when competition is high.

These predictions stem from comparative statics of w_S on τ_1^* and τ_2^* . The comparative statics plots in Figure 10 show that as w_S increases both τ_1^* and τ_2^* increase. These plots reveal that the reason for the positive effect is that internal funds decrease the supplier’s borrowing needs, which lowers the supplier’s marginal cost of providing trade credit to both the large and small retailers.

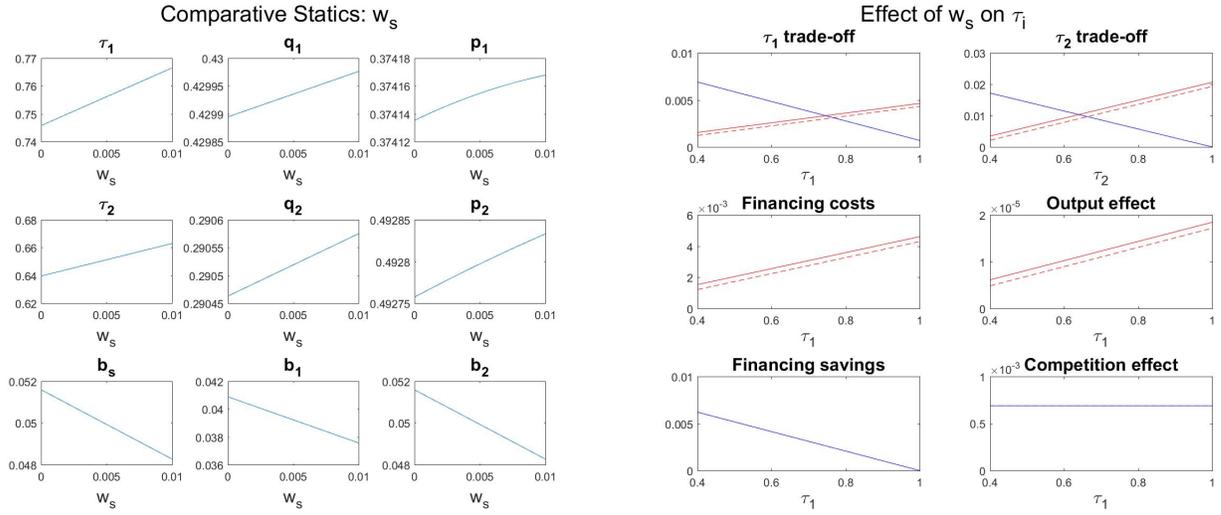


Figure 10: The left group of plots examines how w_s affects the equilibrium. The x-axis represents different values of w_s and y-axis represents the equilibrium variable of interest. The right group of plots examines how ϵ changes the trade-offs that determine equilibrium trade credit. Dashed lines represent an increase in w_s . The top row displays the marginal cost and benefit of taking trade credit, where the left shows τ_1 and right shows τ_2 . Red lines represent the marginal cost and blue lines represent the marginal benefit. The middle row decomposes the marginal cost of τ_1 into financing costs and an output effect. The bottom row decomposes the marginal benefit of τ_1 into financing savings and a competition effect.

The next two sets of plots examine the strength of the effect of w_s on trade credit based on financial constraints. Figure 11 examines the effect of w_s on trade credit when θ_S is high versus low. For both high and low bargaining power customers, the figure reveals that the relationship between w_s and θ_S should be stronger when θ_S is high. This is because the supplier's marginal financing cost is higher when θ_S is high, which means that the value of extra internal funds is also higher. Accordingly, when θ_S is high, an increase in w_s results in a weaker shift in the marginal cost of providing trade credit and weaker trade credit response.

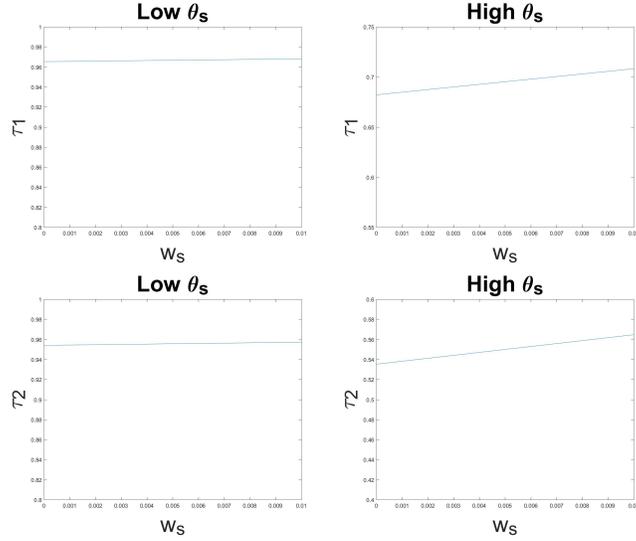


Figure 11: This figure examines how w_S affects equilibrium trade credit under different levels of supplier financial frictions. In each plot, the x-axis represents w_S and y-axis represents trade credit. The top row shows the effect of w_S on τ_1 and bottom row shows the effect of w_S on τ_2 . The left column represents low supplier financial frictions and right column shows high retailer financial frictions.

Figure 12 examines the effect of w_S on τ_1^* when θ_1 is high versus low and the effect of w_S on τ_2^* when θ_2 is high versus low. The plots show that trade credit reacts more strongly when the customer's financial frictions are low. This is because lower financial frictions flatten the marginal benefit curve for extending trade credit. For a given shift in the marginal cost curve, trade credit will react more strongly when the marginal cost curve is flatter. This logic holds for trade credit to both the large and small retailers.

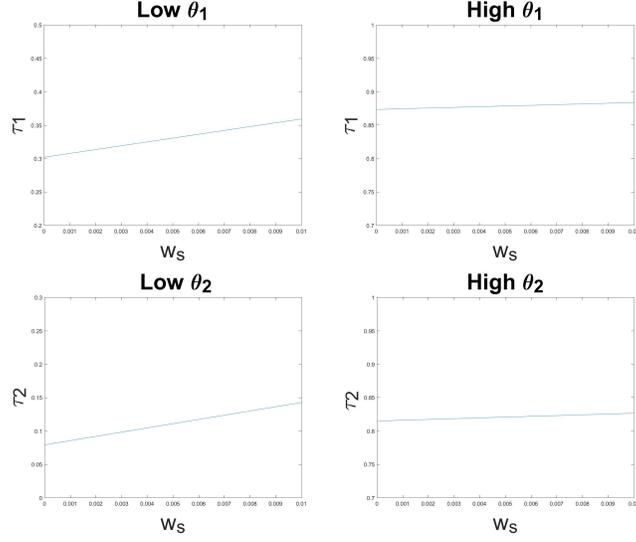


Figure 12: This figure examines how w_S affects equilibrium trade credit under different levels of retailer financial frictions. In each plot, the x-axis represents w_S and y-axis represents trade credit. The top row shows the effect of w_S on τ_1 and bottom row shows the effect of w_S on τ_2 . The left column represents low retailer financial frictions and right column shows high retailer financial frictions.

Figure 13 examines the strength of the effect of w_S on trade credit based on bargaining power and product substitutability. Comparing the top two plots, the figure reveals that for high bargaining power firms the relationship between w_S and τ_1^* should be stronger when ϵ is low. The logic is similar to the case of financial constraints. Lowering ϵ flattens slope on the marginal benefit curve for large retailer taking trade credit. Since the effect of w_S on τ_1^* should be stronger when the marginal benefit curve is flatter, it should be stronger when ϵ is low.

Comparing the bottom two plots, the figure reveals that for low bargaining power firms the relationship between w_S and τ_2^* should be stronger when ϵ is high. This relationship stems from a reaction to τ_1^* , where a weaker effect of w_S on τ_1^* results in a bigger downwards shift in the marginal cost curve on τ_2 and, accordingly, a higher τ_2^* . Since the effect on τ_1^* is weaker when ϵ is high, the effect on τ_2^* should be stronger when ϵ is high.

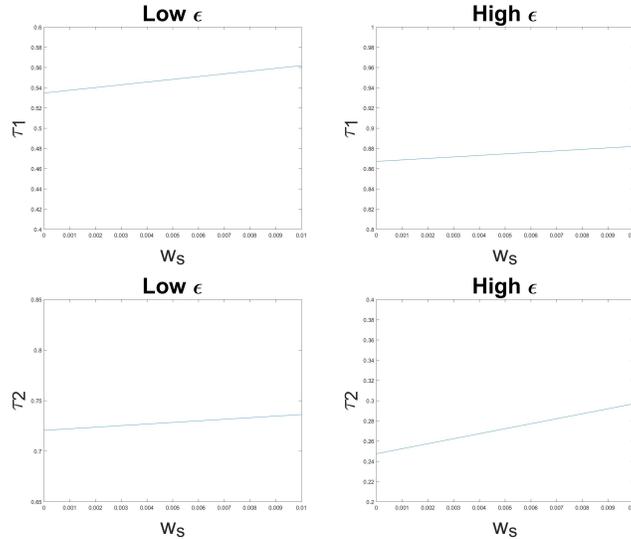


Figure 13: This figure examines how w_S affects equilibrium trade credit under different levels of competition. In each plot, the x-axis represents w_S and y-axis represents trade credit. The top row shows the effect of w_S on τ_1 and bottom row shows the effect of w_S on τ_2 . The left column represents a low competition environment and right column shows a high competition environment.

6 Extensions and discussion

6.1 Dynamics

As this is a static model, there is a question as to whether the mechanism and welfare implications hold up in a dynamic setting. One dynamic factor to consider involves entry and exit from the supplier's customer base over time. Particularly, this gives scope for a large customer to use trade credit to prevent the supplier from transacting with the small customer entirely or from finding new customers. By excluding competitors from the input market, the large customer could become a monopolist, which has clear negative welfare implications.

Another dynamic factor to consider is allowing firms to save over time. In order for trade credit to be an effective tool for large customers, necessary conditions are that the supplier and competitors face financial constraints in the sense that they rely on costly external financing as the marginal source of financing. If these firms can quickly save their way out of requiring costly external financing, then the trade credit tactic will only be effective for a small portion of firms that still face financial constraints. An interesting question involves identifying what must be true about savings or industry dynamics in order for a significant portion of firms to remain financially constrained.

To argue that dynamics don't threaten the validity of the mechanism, I identify several possible features that prevent firms from saving their way out of financial constraints and result in a significant portion of financially constrained firms. One is long lead times on

the supplier's production process. If the supplier needs to finance a portion of inputs several periods in advance, it will be more likely to have outstanding external financial obligations well over any revenues it receives from customers upon delivery in order to cover production costs for future periods.

Now consider an industry of suppliers subject to productivity shocks. A Poisson death shock with a high enough arrival rate could lead to high enough turnover, where a significant portion of firms remain young and have not been alive long enough to save out of their constraints. Similarly, a high enough volatility parameter could increase turnover by pushing firms into low productivity regions so as to induce exit and high turnover. A high volatility parameter could also reduce the value of the relationship between the supplier and small customer, which would reduce the value of the supplier's outside option. This in turn would lower the price that the supplier can charge the large customer, leading to lower supplier profitability and less savings.

Regardless of the reason for the financial constraint, ultimately, all that must be true is that firms rely on costly external financing at the margin. It doesn't matter why they haven't been able to save their way out of their financial constraint, only that it is empirically true.

6.2 Alternative bargaining tools

Bargaining along the trade credit dimension has additional benefits compared to bargaining along other dimensions. The key feature of trade credit is that it affects the supplier's marginal cost of producing for other customers. By interfering with rival's access to low cost inputs, trade credit suppress rival's output quantities and this output reduction constitutes a reduction in competition.

The model incorporates price as another dimension of bargaining that large firms can use in addition to trade credit. In line with the intuition in the last paragraph, the equilibrium outcome is that large customers choose a mix of price and trade credit. The reason why price doesn't work like trade credit is that it serves as a means of splitting the surplus between the supplier and customer but doesn't affect the supplier's contract with other customers.

There is an argument that quality improvement is an alternative bargaining dimension that serves the same role as trade credit in raising the supplier's marginal cost of producing for other customers. One issue is whether implementing quality improvements qualify as a lump sum investment, fixed cost, or marginal cost. In the context of my bargaining model, the first two types of costs would be entirely reflected in a higher input cost for the large customer and therefore would not affect production for other customers.

Now assume that quality improvements do constitute increased marginal costs of production. Even so, quality improvements introduce contracting frictions, as quality

can be difficult to observe and for the customer to enforce. In contrast, trade credit is easily observable and is an action that the customer takes, rather than attempts to elicit from the supplier, so is easy for the customer to control.

Lastly, there may be other means of large customers to suppress competition. For example, large firms could attempt to physically block their competitors from accessing resources or could force suppliers to enter into exclusive supply contracts. However, these tactics are often considered illegal by anti-trust authorities and receive more regulatory scrutiny compared to trade credit.

Anti-trust authorities have not ignored the trade credit feature of supply contracts. However, the discussion has mainly focused on using trade credit to gain an unfair financing advantage over competitors. Using trade credit in the manner that this theory proposes has not been considered.

7 Data

Trade credit data at the customer-supplier level is extremely rare. At the same time, in order to test and control for determinants of trade credit that are customer specific versus supplier specific versus customer-supplier pair specific, this level of detail is extremely important. Many data sources provide firm level trade credit information, but lack information specific to individual customers or suppliers.¹¹ Some sources report information on customer-supplier links, but do not report on trade credit at the customer-supplier level.¹² Other sources provide more detailed information on suppliers' trade credit contracts and their buyer characteristics, but either lack time variation or still contain some form of trade credit aggregation among a customer's suppliers.¹³

Only a few studies have also been able to obtain time varying trade credit at the customer-supplier level. Giannetti, Serrano-Verlarde, and Tarantino (2021) obtain proprietary data from CRIBIS-CRIF on a set of Italian firms. Costello (2019) and Costello (2020) obtain proprietary data from Credit2B on U.S. firms. Freeman (2020) hand collects trade credit balances on U.S. public firms from financial statements, available due to a regulation that requires public firms to disclose high concentrations of credit risks.

I obtain a new trade credit dataset from Experian on U.S. firms from 2008-2016. For U.S. firms interested in monitoring their customer's financial health, Experian provides credit risk information on their customers with the condition they report outstanding credit balances on all U.S. customers every month. Firms have incentive to comply with the reporting requirements in order to continue to receive the credit risk information. Experian's representatives have noted that non-compliance has not been an issue. Experian requires suppliers to report current receivables and past due balances for each

¹¹Compustat; S&P Capital IQ; D&B paydex score; UK disclosures

¹²Compustat Segments; S&P Capital IQ; Bloomberg SPLC; Factset Revere

¹³NSSBF surveys; The World Bank Enterprise Survey

customer. The past due balances are grouped into buckets of 30 day increments, starting at 1-30 days delinquent and ending at 180+ days delinquent.

To construct the firm sample, we provided Experian with a list of 15,000 firms to match to customers in their database. Experian identified all reported supply relationships on these customers and returned monthly receivables information on these firm pairs from January 2008 through December 2016. They additionally returned a snapshot of demographic, financial, and credit risk information in December 2010 on all available customers and suppliers in the sample along with unique firm ID numbers. They provided a matching key in order to match the unique firm ID numbers to company names. However, the matching key only includes customer companies due to an agreement in place with suppliers to keep supplier identities confidential. The firm ID numbers still allows us to track suppliers over time, but this confidentiality requirement prevents us from merging in any firm level information on the supplier side.

In constructing the customer list, we focused on firms with financial information readily accessible from other data sources. We use Compustat for public firms and include all U.S. non-financial firms from 2008-2016. We use S&P Capital IQ and Privco for private firms. S&P Capital IQ data on private firms comes from publicly available information stemming from a regulation that requires all firms with at least 500 common shareholders and \$10 million in revenue to disclose financial information to the SEC. As such, S&P Capital IQ focuses on large private firms. For data on smaller private firms, we use Privco, a company that specializes in private firm data collection.

Since missing data is more common more common for private firms, we impose additional restrictions for including firms from this dataset. From S&P Capital IQ, we include all non-financial U.S. private firms from 2008-2016 with at least 1 observation with non-missing total sales, total assets, cash holdings, accounts payable, and accounts receivable. From Privco, we include all non-financial U.S. private firms from 2010¹⁴ until 2016 with non-missing revenue and employee data from 2010-2013. Where available, I merge financial information on customer firms from Compustat, Capital IQ, and Privco into the trade credit data.

7.1 Variable Definitions

7.1.1 Payment delays

The literature that uses firm level data widely uses a measure called accounts receivable days that represents trade credit and payment timing. This measure scales trade credit by the size of the sales amount and transforms the units from the trade credit share of the sale into days to pay. The formula is $365 / (sales / TC)$. The denominator ($sales / TC$) is called accounts receivable turnover and represents the number of times the customer

¹⁴I use 2010 instead of 2008 because the Privco data starts in 2010.

pays off its balance in a given year. 365 divided by the turnover ratio then gives the average number of days it takes the customer to pay its balance in the year.

The literature that uses similar inter-firm data to this dataset constructs more disaggregated measures. Costello (2020) uses current receivable balance levels. Giannetti et. al (2021) use the proportion of trade credit used in new sales, calculated as the current receivables balance divided by new sales within the month. Hirshleifer et. al (2019) use total past due balances as a proportion of total outstanding balances. This measure is intended to capture a supplier’s private information about a customer’s credit that the market does not possess.

In measuring payment timing, the goal is to construct a data counterpart for the model parameter τ_i , the delayed payment share between each customer-supplier pair. To this end, I construct two measures of payment delinquency. The first is called the *LateShare*, which is very similar to Hirshleifer et. al (2019) in that it is calculated as the share of outstanding receivables that are overdue. Equation 22 displays the formula

$$LateShare_{c,s,m} = \frac{LateBal_{c,s,m}}{TotalBal_{c,s,m}} \quad (22)$$

where subscripts c , s , and m represent customer, supplier, and month. $LateBal_{c,s,m}$ is the total dollars of outstanding receivables between customer c and supplier s in month m that are at least 1 day late. $TotalBal_{c,s,m}$ is the total dollars of outstanding receivables.

The other measure is called days beyond terms (*DBT*) and captures how many days late the customer pays off its credit sales. Equation 23 displays the formula.

$$DBT_{c,s,m} = \sum_{\ell=1}^L w_{c,s,m,\ell} \cdot \ell \cdot 30 \quad (23)$$

$$\text{where } w_{c,s,m,\ell} = \frac{LateBal_{c,s,m+\ell,\ell} - LateBal_{c,s,m+\ell+1,\ell+1}}{CurrentBal_{c,s,m}}$$

Subscripts c , s , m , and ℓ represent customer, supplier, month, and months late bucket. The weight, $w_{c,s,m,\ell}$, is the share of month m ’s current balance that will become ℓ months delinquent ℓ months later. $LateBal_{c,s,m,\ell}$ is the total dollars of outstanding receivables in month m between customer c and supplier s that are between $\ell - 1$ and ℓ months late. $CurrentBal_{c,s,m}$ is the total dollars of outstanding receivables issued in month m between customer c and supplier s . The current receivables balance represents new credit sales within the month between the customer-supplier pair.¹⁵

Before arriving at the final measures, I make a few final adjustments. To mitigate the role of outliers, I drop observations over 180 days delinquent. These observations are highly unusual and amount to less than 1 percent of the data. I also aggregate from

¹⁵Costello (2020) adopts this interpretation. However, in the case of early payment, the current receivables balance will be lower than credit sales.

monthly to annual frequency by taking a value weighted average across months within a year. I do this to avoid complications associated with how to weight observations. One example is that an observation with a balance of \$1 that took 180 days to pay off will have the same weight as a balance of \$1 million that took 30 days to pay. Another example is that the sample will be skewed towards customer-supplier pairs that transact at monthly frequency compared to quarterly or semi-annually because the monthly frequency pairs will have more observations.

Equation gives the aggregation of *LateShare* to year level. Since I construct a value weighted average, each observation's weight is its share of the year's total outstanding receivable balance.

$$LateShare_{c,s,t} = \sum_{m=1}^{12} w_{c,s,m} \cdot LateShare_{c,s,m} \quad (24)$$

$$\text{where } w_{c,s,m} = \frac{TotalBal_{c,s,m}}{\sum_{m=1}^{12} TotalBal_{c,s,m}}$$

Equation gives the aggregation of *DBT* to year level. Since I construct a value weighted average, each observation's weight is its share of the year's total current balance.

$$DBT_{c,s,t} = \sum_{m=1}^{12} w_{c,s,m} \cdot DBT_{c,s,m} \quad (25)$$

$$\text{where } w_{c,s,m} = \frac{CurrentBal_{c,s,m}}{\sum_{m=1}^{12} CurrentBal_{c,s,m}}$$

7.1.2 Bargaining power

My bargaining power measure represents the customer's bargaining priority relative to the supplier's other customers. For each customer-supplier pair, I construct two binary versions of this variable. In the first version, *BPCustRival*, I consider the customer to be high bargaining power if the customer is larger than the supplier's median customer and assign a value of 1 if the customer has high bargaining power and 0 if not. In the second version, *BPCustRival100*, I consider the customer to be high bargaining power if the customer is at least 100 times larger than the supplier's median customer and assign a value of 1 if the customer has high bargaining power and 0 if not. Compared to the first version, the second captures firms that are considerably larger than the supplier's typical customer. While the first version identifies the top half of observations, the second version is more strict and identifies the top 20% of observations.

The literature's standard bargaining power measure captures the customer's bargaining power with the supplier, defined as the employee size of the customer relative to the supplier. I diverge from the literature because that measure captures the customer's

bargaining power with the supplier in absolute terms, while my theory predicts that the form of bargaining power important for trade credit is the customer's sequential bargaining power with the supplier *relative* to the supplier's other customers. For the purpose of comparison with my primary measure, I use the literature's bargaining power measure as my secondary bargaining power measure and refer to this measure as *BPCustSup*.

7.1.3 Financial constraints

In the snapshot of 2010 information, Experian provides a credit score called the financial stability risk score that predicts the likelihood of a firm going bankrupt or experiencing severe financial stress over the next 24 months. Experian uses a variety of information to construct this score, from financial reports to collection agencies to derogatory public records.

The financial stability risk score ranges from 300 to 850, where a higher score means lower risk. Experian additionally groups these credit scores into risk classes ranging from 1 to 5, and labels these categories in increasing order as low (781-850), medium low (721-780), medium (661-720), medium high (601-660), and high (300-600). The sample median is 660. Since this score defines the boundary between the medium and medium high risk categories, the sample will provide a good amount of variation in credit risk.

I construct two measures of financial constraints. *FCSupCust* represents the supplier's financial constraint relative to the customer's and is constructed as the supplier's risk class less the customer's risk class. High values mean that the supplier is a higher credit risk relative to the customer and suggests that the supplier should face more severe financial constraints and borrowing costs relative to the customer. *FCRival* represents rival customer financial constraints and is constructed as the median risk class of the supplier's other customers. High values mean that rivals are higher credit risks relative to the supplier and suggests that rivals should face more severe financial constraints and borrowing costs relative to the supplier. Although prior studies sometimes define financial constraints in a binary sense, where a risk class of 4 or 5 signals a financially constrained firm, I do not adopt this approach because I run into multicollinearity issues in the regressions. I argue that moving from one risk class to another signals a meaningful change in a firm's credit risk. In the documentation that Experian provided us, this is empirically true. Specifically, Experian provided tables showing that firms in higher risk classes default more often on their obligations.

7.1.4 Product substitutability

I measure of product substitutability among customers in two ways. The first measure is whether or not the supplier sells to rivals. For each customer-supplier pair, *Rival* is

a binary variable that equals 1 if the supplier sells to another customer within the same 4 digit SIC industry code and 0 if not. For robustness, I also construct a continuous version that equals the total number of rivals that the supplier sells to in the same 4 digit SIC industry code. The second measure is a commonly used industry classification of product market differentiation from Rauch (1999). For each customer-supplier pair, *StandInd* is a binary variable that equals 1 if the customer’s industry is considered standardized and 0 if not. A value of 1 indicates that the customer experiences higher product substitutability with its rivals.

7.2 Summary statistics

In this section I present summary statistics on the trade credit database. The database consists of 916 unique suppliers, 6,685 unique customers, and 36,309 unique customer-supplier relationships. Tables 2 and 3 show statistics on supplier level and customer level variables, respectively. The typical supplier and typical customer are similar in terms of size, as measured by the number of employees, and financial constraints, as measured by the credit score and risk class category variables. Table 4 shows statistics on customer-supplier level variables. Approximately half of the observations involved late payment, as evidenced by a median *DBT* and *LateShare* barely above 0. Trade credit rises significantly within the top half of the sample, resulting in a mean *DBT* of 7.1 days and *LateShare* of .28.

	Count
Number of Suppliers	916
Number of Customers	6,685
Number of Customer-Supplier Pairs	36,309

Table 1: Summary Statistics

	N	Mean	Median	sd	p25	p75
Risk Class	627	3.305	3	1.291	2	4
Employee Size	530	2,581	70	15,574	20	300
Number of Customers	2,212	39.33	9	134.7	3.167	23.5

Table 2: Supplier Characteristics

	N	Mean	Median	sd	p25	p75
# Rivals (SIC4)	9,325	76.28	14.42	152.1	5	47.7
Rival (SIC4)	9,325	0.853	0.93	0.215	0.8	1
Risk Class	7,257	3.467	4	1.217	3	5
Employee Size	6,917	2,534	85	14,167	20	478
Cash/Assets	3,997	0.24	0.135	0.256	0.0519	0.345
Book Lev.	3,997	0.213	0.145	0.235	0.0335	0.317
Number of Suppliers	10,865	7.854	4.548	10.83	2	9.27

Table 3: Customer Characteristics

	N	mean	p50	sd	p25	p75
LateShare	697,755	0.286	0.172	0.318	0	0.483
DBT	686,805	7.110	0.271	130.1	0	7.954
RivalFC	462,872	3.795	3.768	0.258	3.610	3.950
FCSupCust	232,979	0.477	0	1.534	0	1
BPCustRival	352,254	0.661	1	0.473	0	1
BPCustRival100	352,005	0.123	0	0.328	0	0

Table 4: Firm Pair Characteristics

8 Empirical facts

8.1 Delinquency and customer size

In this section, I use the data to document the relationship between delinquency and customer size and show why it is puzzling. Figure 14 plots delinquency by customer size deciles, where size is measured by the number of employees.

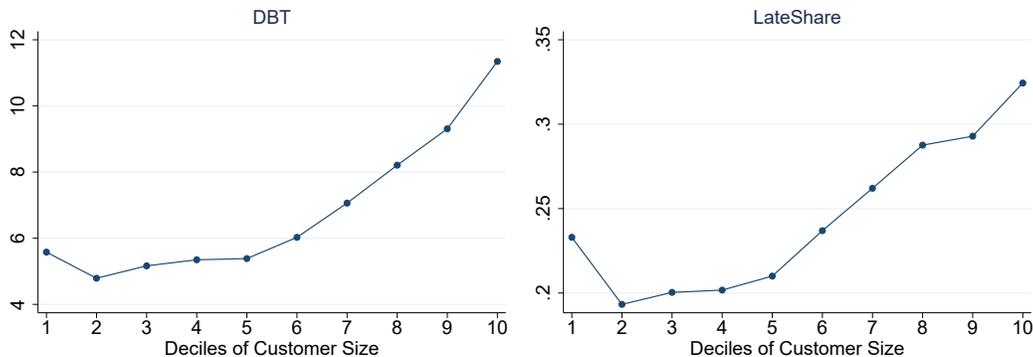


Figure 14: This figure plots the mean delinquency over deciles of customer size. Customer size is measured by the customer's employee size category. The left panel measures delinquency using *DBT*, while the right panel measures delinquency using *LateShare*.

Figure 14 reveals that delinquency increases with customer size. This pattern is puzzling because larger customers are likely less constrained relative to their suppliers and less constrained customers should pay more promptly.

Figure 15 provides empirical support for this argument, confirming that the relationship between delinquency and customer size is puzzling. The left chart plots the supplier's financial constraint relative to the customer's over customer size and confirms that relative financial constraints indeed increase with customer size. The right chart plots delinquency over the supplier's financial constraint relative the customer's. Consistent with the traditional theory, the chart reveals a negative relationship between delinquency and relative financial constraints. Looking at financial constraints alone, the data suggests that the relationship between delinquency and customer size should be negative.

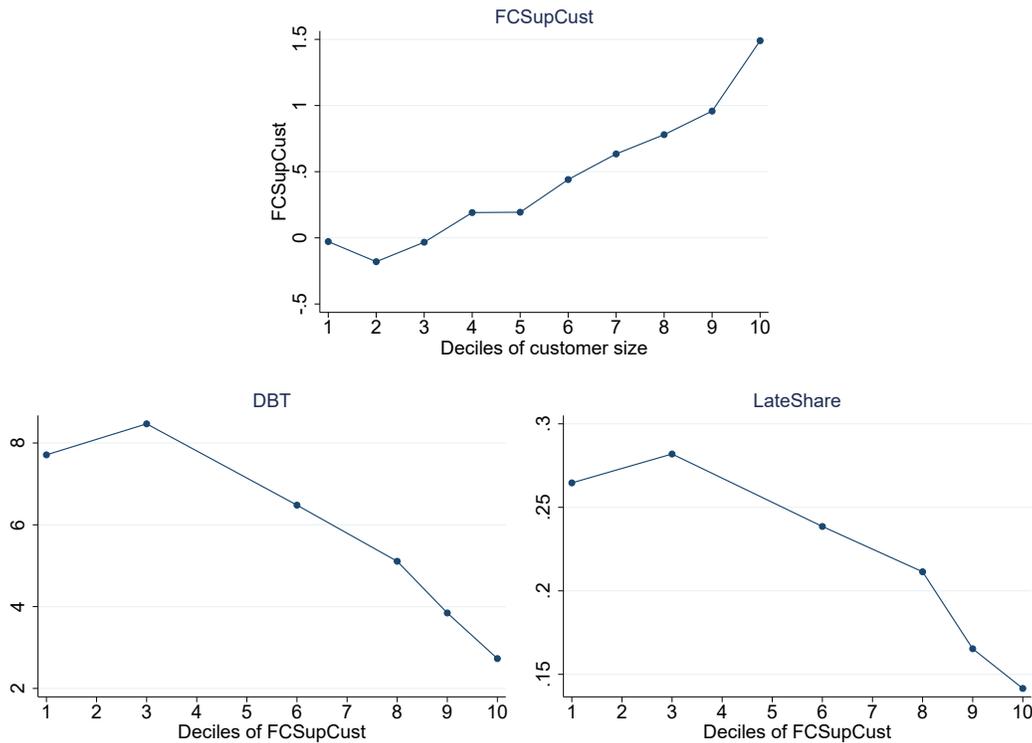


Figure 15: The top panel of this figure plots the mean relative financial constraints over deciles of customer size. The bottom panels plot the mean delinquency over deciles of relative financial constraints. Relative financial constraints are measured using *FCSupCust*. The bottom left panel measures delinquency using *DBT*, while the bottom right panel measures delinquency using *LateShare*.

8.2 Delinquency and bargaining power

Assuming customers gain bargaining power as they become larger, the size pattern could be a result of a positive effect of size on delinquency via bargaining power that counteracts the negative effect of size on delinquency via financial constraints. Figure 16 shows that the theory's argument holds empirically. The left chart plots bargaining power over customer size and confirms that bargaining power indeed increases in size. This might

seem like a mechanically induced relationship, since bargaining power is based on size, rendering the plot unnecessary. However, since bargaining power is based on a relative, rather than absolute size measure, a positive relationship is not guaranteed mechanically. The right chart plots delinquency over customer bargaining power and reveals a positive relationship between delinquency and customer bargaining power.

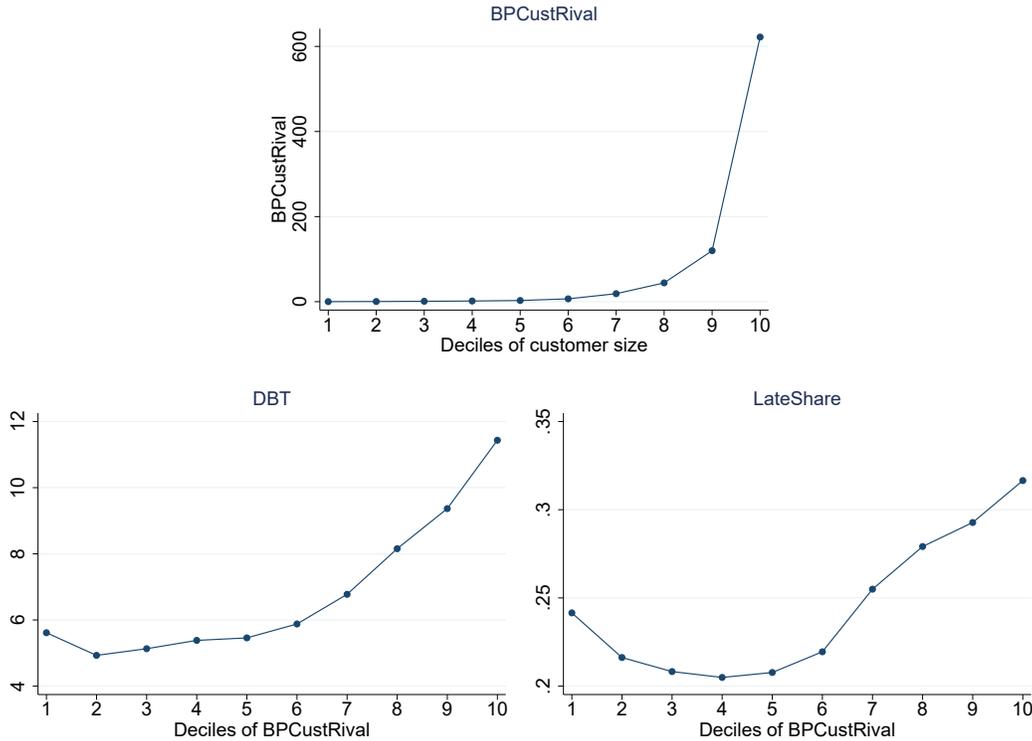


Figure 16: The top panel of this figure plots the mean bargaining power over deciles of customer size. The bottom panels plot mean delinquency over deciles of bargaining power. The bottom left panel measures delinquency using *DBT*, while the bottom right panel measures delinquency using *LateShare*. Bargaining power is measured using the continuous version of *BPCustRival*.

This theory also suggests that the customer’s bargaining power relative to rivals is what drives large customers to delay payment, not the literature’s standard measure of bargaining power relative to the supplier. Figure 17 displays the relationship between delinquency and bargaining power, where the left column uses the measure relative to the supplier and the right column uses the measure relative to rivals. Although both relationships are generally positive, the measure relative to rivals appears more aligned with the size pattern, suggesting that the relative measure is the driving force.

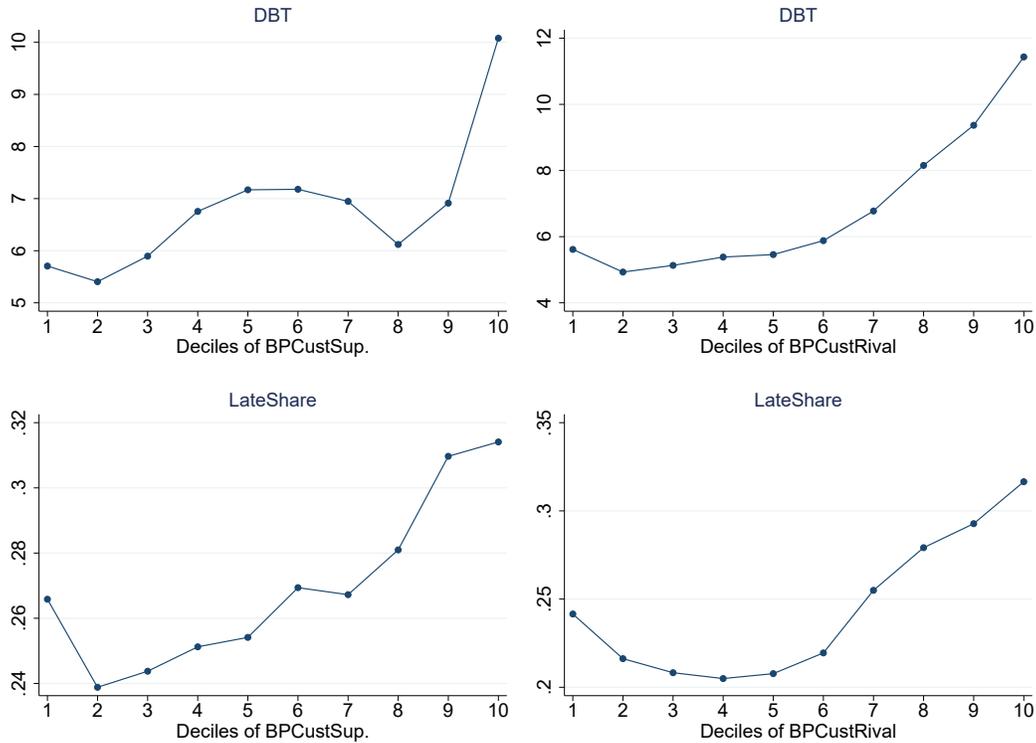


Figure 17: This figure plots the mean delinquency over deciles of bargaining power. Delinquency is measured using *DBT* in the top panels and *LateShare* in the bottom panels. Bargaining power is measured using *BPCustSup* in the left panel and *BPCustRival* in the right panels.

8.3 High bargaining power customers

Seeing that delinquency tends to increase with customer bargaining power, this section explores what drives high bargaining power customers to delay payment. Specifically, I examine if their payment behavior is consistent with the theory proposed in this paper. The theory predicts that we should expect high bargaining power customers to pay later when product substitutability is high, both in absolute terms and relative to low bargaining power customers.

Figure 18 plots the delinquency for firm pairs with high versus low bargaining power customers and high versus low product substitutability. In each chart, the left columns focus on firm pairs with high bargaining power customers and focus on firm pairs with low bargaining power customers. Blue columns represent low product substitutability and red columns represent high substitutability. Looking at the *DBT* measure, the patterns are consistent with the theory. High bargaining power customers delay payment when product substitutability is high, both in absolute terms and relative to low bargaining power customers. Looking at the *LateShare* measure, the patterns do not as robustly support the theory.

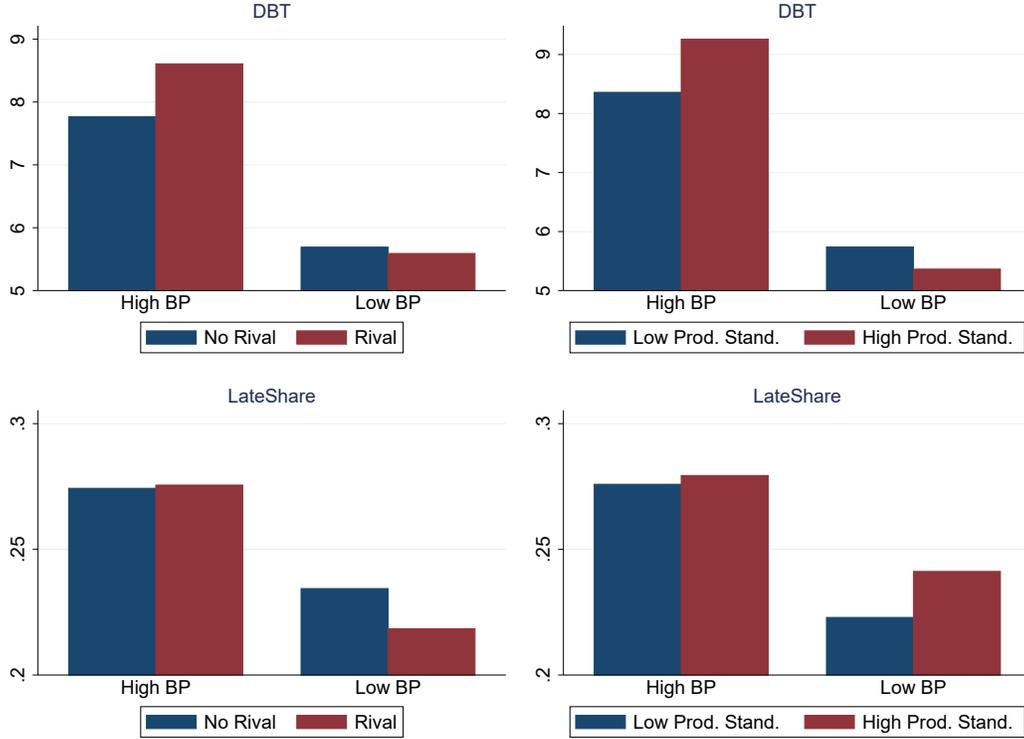


Figure 18: This figure plots the mean delinquency by product substitutability and bargaining power. In each panel, the left bars contain customer-supplier pairs with a high bargaining power customer, while right bars do not. Blue bars represent low product substitutability, while red columns represent high product substitutability. Delinquency is measured using *DBT* in the top panels and *LateShare* in the bottom panels. Product substitutability is measured using *Rival* in the left column and *Prod. Stand.* in the right column. Bargaining power is measured using *BPCustRival*.

9 Testing predictions with equilibrium relationships

To test the model's predictions, I estimate regression equations with a large set of fixed effects that help control for a wide variety of factors. Equation 26 states the base specification.

$$DBT_{c,s,t} = \beta_0 + \beta_1 FCSupCust_{c,s,0} + \beta_2 FCRival_{c,s,0} + \beta_3 BPCustRival_{c,s,0} + \theta \mathbf{Z} + \alpha_{c_i,s,t} + \epsilon_{c,s,t} \quad (26)$$

The dependent variable $DBT_{c,s,t}$ represents days beyond terms between customer c and supplier s in year t . The independent variables $FCSupCust$ and $FCRival$ represent financial constraints, where the former is the customer relative to the supplier and latter is rival customers. $BPCustRival$ represents relative bargaining power between the customer and rival customers. \mathbf{Z} denotes a vector of controls.

I include triple interactions of customer industry c_i , supplier s , and year t fixed effects, where the customer's industry is at the 4 digit SIC code level. These fixed effects control

for the supplier's cost of providing credit to customers in the same industry over time and the customer industry's demand for credit over time. This means that I exploit variation in payment timing to different customers within the same industry from the same supplier in the same year.

Throughout this section, all specifications are robust to using two other specifications of fixed effects. The first is a combination of an interaction of customer and year fixed effects along with supplier and year fixed effects. The second is a combination of an interaction of customer x supplier fixed effects along with year fixed effects. Note that the second specification limits the variables that I can include in the regression because any variable that is customer-supplier specific and time invariant will be consumed by the customer x supplier fixed effects.

In addition to fixed effects models, since a non-negligible portion of the dependent variable values are 0, I employ a censored regression model. While OLS would tend to underestimate coefficients, a censored regression model acknowledges that the delinquency values are bounded by 0 and estimates unbiased coefficients. Accordingly, I include tobit specifications throughout this section.

Tables 5 shows the results of estimating equation 26 with only financial constraints variables. To test prediction 1, I test the signs on the coefficients of *FCSupCust*. Both the traditional theories and this theory predict that the signs should be negative, indicating that delinquency decreases when the supplier is more financially constrained relative to the the customer. Consistent with the theories, the coefficients on *FCSupCust* are negative and statistically significant across specificaitons. While these results do not shed light on the validity of the theory put forth in this paper, they confirm that the traditional theory holds in the Experian dataset.

To test prediction 2, I test the signs on the coefficients of *FCRival*. The theory predicts that the signs should be negative, indicating that delinquency decreases when the supplier's other customers are more financially constrained. The coefficients on *FCRival* are either statistically insignificant or negative and statistically significant. While the results do not contradict the theory's prediction, they do not offer robust support either.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Tobit	(4) Tobit
FCSupCust	-1.400*** (0.0489)	-0.994*** (0.110)	-1.718*** (0.0749)	-0.980*** (0.112)
FCRival			-1.165** (0.469)	-6.089*** (0.689)
Cust. Book Lev.		1.572** (0.626)		2.086*** (0.570)
Cust. Cash/Assets		-3.075*** (0.640)		-5.085*** (0.742)
Observations	187,704	87,087	196,177	87,087
R-squared	0.544	0.669		
Controls	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: This table examines the effect of financial constraints on *DBT*. The results are obtained by estimating equation 26, excluding the *BPCustRival* explanatory variable. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

Next, I focus on bargaining power as a determinant of delinquency. Table 6 shows the results of estimating equation 26 with both the bargaining power and financial constraints variables. The results show that coefficients on *BPCustRival* are positive and statistically significant across all specifications, confirming prior results on the effect of bargaining power on delinquency. To confirm that these results are robust to using a different size threshold to define a high bargaining power customer, I include the variable *BPCustRival100*. As expected, the coefficients remain positive and statistically significant and increase in magnitude. These results confirm the positive relationship between bargaining power and delinquency.

Also of interest are the coefficients on financial constraints. Since the financial constraint and bargaining power variables are likely correlated with each other, it's possible that bargaining power is the primary driver of delinquency and the financial constraint results in table 5 are a manifestation of a correlation between the two. Supporting the theory's predictions, the coefficients on *FCSupCust* remain negative and statistically significant and the coefficients on *FCRival* become more robustly negative and statistically significant.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Tobit	(4) Tobit	(5) Fixed effects	(6) Tobit
BPCustRival	1.487*** (0.154)	1.442*** (0.375)	6.788*** (0.275)	6.675*** (0.550)	1.016*** (0.375)	5.137*** (0.551)
BPCustRival100					3.470*** (0.445)	7.248*** (0.425)
FCSupCust	-1.319*** (0.0577)	-1.023*** (0.130)	-1.557*** (0.0852)	-0.942*** (0.126)	-0.851*** (0.130)	-0.571*** (0.127)
FCRival			-0.905* (0.538)	-5.925*** (0.786)		-4.630*** (0.783)
Cust. Book Lev.		1.753** (0.751)		2.573*** (0.624)	1.440* (0.753)	2.072*** (0.623)
Cust. Cash/Assets		-2.757*** (0.732)		-2.467*** (0.835)	-2.346*** (0.731)	-1.619* (0.831)
Observations	145,296	70,118	151,568	70,118	70,064	70,064
R-squared	0.584	0.700			0.702	
Sup. x Cust. Ind x Year FE	YES	YES	NO	NO	YES	NO
Controls	NO	YES	NO	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: This table examines the effect of bargaining power on *DBT*. The results are obtained by estimating equation 26. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

Finding a positive relationship between bargaining power and delinquency is not definitive support of the theory's predictions because the sign is not robust to all parameter combinations in the model. To more directly test the model's predictions on bargaining power, I test predictions 3a and 3b.

Prediction 3a states that the relationships between bargaining power and delinquency should be positive for financially unconstrained customers. To test this relationship, I confining the sample to customer-supplier pairs with a financially unconstrained customer and estimate equation 26. Following Giannetti et al (2021), I define a financially unconstrained customer as a customer with risk class of 3 or less. Table 8 displays the results.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Tobit	(4) Tobit	(5) Fixed effects	(6) Tobit
BPCustRival	1.064*** (0.224)	1.455** (0.588)	5.425*** (0.385)	5.359*** (0.804)	1.212** (0.589)	4.548*** (0.809)
BPCustRival100					3.468*** (1.171)	6.235*** (0.939)
FCRival			0.712 (0.863)	-6.664*** (1.522)		-5.910*** (1.525)
FCSupCust	-1.087*** (0.150)	-1.182*** (0.397)	-1.002*** (0.169)	-0.445 (0.289)	-1.036*** (0.394)	-0.337 (0.288)
Cust. Book Lev.		1.683 (1.540)		2.238*** (0.833)	1.588 (1.542)	2.045** (0.833)
Cust. Cash/Assets		-1.767 (1.235)		0.334 (1.197)	-1.653 (1.231)	0.732 (1.194)
Observations	56,884	20,067	57,532	20,067	20,055	20,055
R-squared	0.634	0.742			0.743	
Controls	NO	YES	NO	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: This table examines the effect of bargaining power on *DBT* for customer-supplier firms with a financially unconstrained customer. A financially unconstrained customer is defined as a customer firm with a risk class of 3 or lower. The results are obtained by estimating equation 26 on this subsample. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

Prediction 3b states that the relationship between customer size and delinquency should be more positive for high bargaining power customers. Table 8 shows the results of estimating equation 26 with an interaction effect between bargaining power and customer size, where customer size is defined as the log of the number of employees. Since the bargaining power measure is based on size, I effectively test if there is a nonlinear effect of customer size on delinquency, where the theory predicts that there should be a more positive effect when customer size is high. The results show that the effect of customer size is negative when bargaining power is low but positive when bargaining power is high.

VARIABLES	(1) Fixed effects	(2) Tobit	(3) Fixed effects	(4) Tobit
Cust. Size	-0.203** (0.0937)	-0.358** (0.152)	-0.322 (0.221)	-0.197 (0.288)
Cust. Size x BPCustRival	1.226*** (0.105)	2.269*** (0.167)	1.217*** (0.249)	1.812*** (0.320)
Cust. Size x BPCustRival100			-0.251 (0.440)	0.145 (0.396)
BPCustRival	-6.015*** (0.470)	-8.771*** (0.790)	-6.278*** (1.172)	-7.769*** (1.620)
BPCustRival100			3.588 (4.373)	1.526 (4.017)
FCSupCust	-1.065*** (0.0580)	-1.142*** (0.0856)	-0.734*** (0.131)	-0.401*** (0.128)
Cust. Book Lev.			1.286* (0.753)	1.742*** (0.624)
Cust. Cash/Assets			-1.602** (0.739)	-0.631 (0.836)
FCRival		-4.061*** (0.555)		-7.653*** (0.839)
Observations	145,296	151,568	70,064	70,064
R-squared	0.587		0.703	
Controls	NO	NO	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: This table examines the effect of customer size on DBT across different levels of bargaining power. The results are obtained by estimating equation 26 with an interaction effect between bargaining power and customer size. . Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

Next, I compare my measure of bargaining power with the literature’s standard measure. One of the theory’s predictions is that the type of bargaining power that is important for delinquency is the customer’s bargaining power relative to the supplier’s other customers, rather than purely with the supplier as the literature commonly uses. To address this prediction, equation 27 includes the literature’s bargaining measure for comparison with my bargaining power measure.

$$DBT_{c,s,t} = \beta_0 + \beta_1 BPCustRival_{c,s,0} + \beta_2 BPCustSup_{c,s,0} + \theta Z + \alpha_{s,t,i} + \epsilon_{c,s,t} \quad (27)$$

Estimating equation 27 with each bargaining power measure individually, the coefficient on each is positive and statistically significant. Including both bargaining power measures in the equation sheds light on which measure drives the result. If the effect of the literature’s bargaining power measure on delinquency is actually driven by my bargaining measure, we should find that the coefficient on *BPCustRival* remains positive and statistically significant, while the coefficient on *BPCustSup* becomes negative. This suggests that the positive effect of bargaining power on delinquency is driven by bargaining power relative to competitors, not bargaining power relative to the supplier.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) Tobit	(5) Tobit
BPCustRival100			2.751*** (0.992)		8.047*** (0.657)
BPCustRival		1.027 (0.699)	0.960 (0.698)	7.091*** (0.853)	5.834*** (0.850)
BPCustSup	2.768*** (0.528)	2.362** (1.088)	0.873 (1.197)	0.760 (0.591)	-0.884 (0.601)
FCSupCust		-0.647** (0.260)	-0.550** (0.261)	-0.688*** (0.192)	-0.488** (0.191)
FCRival				-1.124 (1.279)	0.0214 (1.274)
Cust. Book Lev.		1.345 (0.980)	1.205 (0.982)		
Cust. Cash/Assets		-2.485 (1.516)	-2.386 (1.512)		
Observations	76,074	34,973	34,939	34,973	34,939
R-squared	0.662	0.764	0.765		
Sup. x Cust. Ind x Year FE	YES	YES	YES	NO	NO
Controls	NO	YES	YES	NO	NO

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: This table compares the effects of two different bargaining power measures on DBT. The results are obtained by estimating equation 27. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

Next, I test the model's predictions on the interaction between product substitutability and bargaining power in their effect on delinquency. First, I split the sample by levels of product substitutability. I estimate equation 28 to determine the effect of bargaining power on delinquency across the different subsamples. I examine the results using both measures of product substitutability, *Rival* and *StandInd*, and both measures of bargaining power, *BPCustRival* and *BPCustRival100*.

$$DBT_{c,s,t} = \beta_0 + \beta_1 BPCustRival_{c,s,0} + \beta_2 BPCustRival100_{c,s,0} + \theta Z + \alpha_{c_i,s,t} + \epsilon_{c,s,t} \quad (28)$$

Table 10 shows the results. The model predicts that the coefficients on bargaining power should be stronger when product substitutability is high. The results are generally consistent with the model predictions, but are more robust when using the bargaining power measure with the stricter relative size threshold, *BPCustRival100*.

VARIABLES	(1) SIC4 Rival	(2) SIC4 Rival	(3) No Rival	(4) No Rival	(5) StandInd	(6) StandInd	(7) DiffInd	(8) DiffInd
BPCustRival100		7.400*** (0.498)		7.393*** (0.727)		8.472*** (1.015)		6.406*** (0.517)
BPCustRival	6.465*** (0.599)	5.068*** (0.599)	6.465*** (1.126)	4.421*** (1.133)	5.857*** (1.224)	4.467*** (1.218)	6.149*** (0.739)	4.636*** (0.743)
FCSupCust	-1.902*** (0.155)	-1.543*** (0.155)	-0.0536 (0.214)	0.313 (0.216)	-0.792** (0.308)	-0.285 (0.311)	-0.656*** (0.159)	-0.281* (0.160)
FCRival	-9.321*** (1.038)	-7.614*** (1.032)	1.916 (1.240)	3.269*** (1.241)	-5.617*** (1.845)	-3.736** (1.835)	-7.637*** (0.972)	-6.456*** (0.970)
Cust. Book Lev.	2.889*** (0.676)	2.303*** (0.675)	1.758 (1.396)	1.296 (1.394)	4.316*** (1.420)	4.010*** (1.414)	2.077** (0.832)	1.536* (0.832)
Cust. Cash/Assets	-3.587*** (0.871)	-2.703*** (0.866)	-2.942 (2.234)	-2.380 (2.226)	-6.996*** (1.728)	-5.698*** (1.716)	-3.183*** (1.134)	-2.280** (1.130)
Observations	46,425	46,417	23,693	23,647	13,024	13,012	44,169	44,139

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: This table examines the effect of bargaining power on DBT across subsamples with different levels of product substitutability. The results are obtained by estimating equation 28. All specifications are tobit random effects regressions with year dummies. Column (1) restricts the sample to customer-supplier pairs where the supplier has another customer in the same 4 digit SIC industry as the customer. Column (2) restricts the sample to customer-supplier pairs where the supplier does not have another customer in the same 4 digit SIC industry as the customer. Column (3) restricts the sample to customer-supplier pairs where the customer's industry is considered standardized by the Racuh (1999) classification. Column (4) restricts the sample to customer-supplier pairs where the customer's industry is not considered standardized by the Racuh (1999) classification.

$$DBT_{c,s,t} = \beta_0 + \beta_1 PS + \theta Z + \alpha_{c_i,s,t} + \epsilon_{c,s,t} \quad (29)$$

Second, I do the reverse of the last exercise, where I split the sample by levels of bargaining power. I estimate equation 29 to determine the effect of product substitutability (PS) across the different subsamples. I use *Rival* and *StandInd* as measures of product substitutability. Table 17 shows the results. Consistent with the model's predictions, the coefficients on *Rival* and *StandInd* are more positive when bargaining power is high compared to when bargaining power is low. However, inconsistent with the model's predictions, the coefficients on these two variables in the no bargaining power sample are positive, while the model predicts that they should be negative.

VARIABLES	(1) High BP	(2) High BP	(3) High BP	(4) BP	(5) BP	(6) BP	(7) No BP	(8) No BP	(9) No BP
StandInd	2.985*** (0.988)			0.221 (0.490)			-0.624 (1.299)		
Rival (SIC4)		2.538*** (0.691)			2.382*** (0.357)			0.555 (1.134)	
# Rivals (SIC4)			0.0858*** (0.0244)			0.0339*** (0.00962)			-0.0 (0.0)
FCSupCust	1.573*** (0.316)	0.928*** (0.297)	1.007*** (0.295)	-0.579*** (0.149)	-0.993*** (0.137)	-0.896*** (0.136)	-1.680*** (0.428)	-1.691*** (0.361)	-1.6 (0.3)
FCRival	-6.418*** (1.856)	-4.119** (1.804)	-3.713** (1.839)	-6.641*** (0.907)	-4.441*** (0.850)	-4.713*** (0.869)	-11.18*** (2.705)	-8.402*** (2.396)	-9.6 (2.3)
Cust. Book Lev.	0.815 (2.122)	0.474 (1.855)	0.764 (1.857)	2.545*** (0.970)	2.514*** (0.833)	2.465*** (0.835)	2.707** (1.096)	2.582*** (0.952)	2.65 (0.9)
Cust. Cash/Assets	7.669** (3.049)	4.723* (2.828)	4.183 (2.853)	-4.272*** (1.098)	-3.092*** (0.999)	-3.443*** (1.033)	-4.501** (1.953)	-2.461 (1.596)	-1.6 (1.6)
Observations	13,835	15,943	15,943	51,267	62,117	62,117	5,926	8,001	8,001
Standard errors in parentheses									
*** p<0.01, ** p<0.05, * p<0.1									

Table 11: This table examines the effect of product substitutability on DBT across subsamples with different levels of bargaining power. The results are obtained by estimating equation 29. All specifications are tobit random effects regressions with year dummies. High BP columns restrict the sample to firm pairs where $BPCustRival_{100}$ equals 1. BP columns restrict the sample to firm pairs where $BPCustRival$ equals 1. No BP columns restrict the sample to firm pairs where $BPCustRival$ equals 0.

10 Testing predictions with the QuickPay reform

I conduct another empirical exercise in order to examine whether changes in the equilibrium over time are consistent with model implications. Specifically, I test predictions 5a, 5b, and 5c, which involve the effect of the supplier's internal funds on delinquency. Instead of estimating the effect directly, I exploit a plausibly exogenous shock to the supplier's internal funds. The reasons for using this approach are twofold. First, due to supplier confidentiality, we don't observe information on supplier cash flow. Second, there are endogeneity concerns with estimating the effect directly. For example, investment opportunities and debt are likely correlated with both delinquency and cash.

In line with the traditional theories, the model predicts that treated suppliers should allow greater payment delays relative to untreated suppliers after the reform (prediction 5a). In contrast with traditional trade credit theories, the model predicts that treatment effect should be strongest when the supplier faces high financial frictions and the customer faces low financial frictions (prediction 5b). Lastly, the model predicts that in low competition environments, treated suppliers should extend more trade credit to high bargaining power customers. In high competition environments, treated suppliers should allow greater payment delays from low bargaining power customers (prediction 5c).

10.1 The QuickPay reform

In order to help employment recover from the 2008 financial crisis, the federal government implemented a reform in 2011 called QuickPay that accelerated payments to federal government contractors. The reform targeted small businesses under the assumption that small businesses would have a higher propensity to use the funds to hire new employees

The reform required federal agencies to pay its small business contractors within 15 days, instead of the typical 30 days. Although getting paid 15 days sooner might not seem large, the reform amounted to approximately \$70 billion per year in accelerated payments. Barrot and Nanda (2020), the only other paper to study this reform, find that the reform was effective in alleviating financial constraints and incentivizing firms to increase employment.

10.2 Data

For the purpose of analyzing the QuickPay reform, I also include government agencies as customers. I identify government agencies using the Federal Procurement Data System (FPDS), which is available due to the Federal Funding Accountability and Transparency Act of 2006. This piece of legislation required that the federal government report information on federal awards, including federal contracts, and contains data from 2000 to present.

As a result, the federal government reports features of its contracts including but not limited to the contract's amount and date, the name of the contracting government department and agency, the name of the contract recipient, the contract recipient's NAICS industry code, and whether or not the contract recipient qualifies as a small business.

10.3 Treatment definition

I follow Barrot and Nanda (2020) for identifying government suppliers affected by the QuickPay reform. A supplier must meet several criteria in order to receive accelerate payment under the QuickPay program. These criteria are:

1. The supplier must be awarded a government contract in 2009, 2010, or 2011.
2. The supplier must be classified as a small business. The reform used the Small Business Administration's (SBA) thresholds to identify small businesses, set in terms of industry specific revenue and employee amounts. These range from from \$0.75 million to 38.5 million on the revenue dimension and 100 to 1,500 on the employee dimension.
3. The supplier must have an initial contract with terms longer than 15 days. This excludes contracts that were already being paid within 15 days, such as a type of con-

tract called cost-plus contracts, contracts involving delivery of meat food products, fresh or frozen fish, perishable commodities, and dairy products, and Department of Defense contracts with small businesses categorized as “disadvantaged”.

I define a treated customer-supplier pair as one with both a non-government customer and supplier that meets the criteria required to receive accelerated payment under the QuickPay reform. However, due to supplier confidentiality, I cannot identify treated suppliers in the dataset simply by merging in a dummy variable. Instead, Experian internally matched the list of treated firms with with suppliers in the sample and returned a list of the supplier ID numbers for firms that matched.

Table 12 shows the number of unique suppliers, customers, and customer-supplier pairs in the sample that were treated versus untreated. The low number of treated suppliers sticks out and may appear surprising. However, as a share of the total number of suppliers, this is expected because it is consistent with the reform’s footprint as a share of the total economy. While this raises concerns about external validity, it doesn’t constitute an unreasonably small treated sample because the unit of observation is at the customer-supplier level, not supplier level. As a result, the number of treated units is the number of treated customer-supplier pairs, which totals 922.

	Untreated	Treated	Treated Share
Number of Suppliers	879	37	4.0%
Number of Customers	6,680	623	8.5%
Number of Customer-Supplier Pairs	35,387	922	2.5%

Table 12: Firm counts

	Untreated		Treated	
	Mean	Median	Mean	Median
TC (Days Beyond Terms)	7.810	1.215	4.846	0
Cust. Credit Score	616.3	631	614.0	620
Sup. Credit Score	728.6	729	756.1	751
RelFC (Sup. to Cust.)	0.845	0.851	0.814	0.820
Cust. Employee Size	496.6	374.5	550.7	749.5
Sup. Employee Size	275.0	74.50	136.2	74.50
BP (Binary)	0.506	1	0.481	0

Table 13: Summary statistics

10.4 Methodology

I now examine how the QuickPay reform affected payment timing throughout the supply network. I first examine the overall impact of the reform. To do so, I perform a difference in differences estimation, where I compare the difference in delinquency between treated and untreated customer-supplier pairs before versus after the reform. Equation 30 displays the baseline specification

$$DBT_{c,s,t} = \beta_0 + \beta_1 Treated_s \cdot Post_t + \theta \mathbf{Z} + \psi_t + \alpha_{c,s} + \epsilon_{c,s,t} \quad (30)$$

where subscripts c , s , and t denote customer, supplier, and year. $DBT_{c,s,t}$ represents delinquency, where I use days beyond terms as the primary measure. $Treated$ is a dummy variable for if firm pair is treated, $Post$ is a dummy variable that equals 0 if the observation occurred in 2010 or 2011 and 1 if the observation occurred in 2012 or 2013, and \mathbf{Z} is a vector of controls. I represent time fixed effects with ψ_t and customer-supplier fixed effects with $\alpha_{c,s}$.

Customer-supplier fixed effects capture any pre-existing differences in delinquency between treated and untreated firm pairs, removing the need to estimate the coefficient on a separate $Treated$ dummy variable. Similarly, time fixed effects capture any changes in delinquency across time that are common to both treated and untreated firm pairs, removing the need to estimate the coefficient on a separate $Post$ variable.

The coefficient β_1 is the difference in differences estimator, containing the average treatment effect of the treated. Specifically, this coefficient captures the difference in delinquency between treated and untreated customer-supplier pairs before and after the reform. A positive coefficient suggests that the reform customers delay payment to affected suppliers. The identifying assumption is that there are no omitted variables that affect delinquency differently in treated versus untreated customer-supplier firm pairs across time, from before to after the reform.

10.5 Full sample results

Table 14 displays the results from estimating equation 30. Column (1) uses OLS, column (2) incorporates time and fixed effects, and column (3) includes controls. I do not include controls for customer financial information, as I did in previous sections, because the sample drops by half and is already small to begin with.

The first row contains the difference in differences estimator and is the main outcome of interest. Across all specifications, the coefficients are positive and statistically significant, suggesting that reform influenced customers to delay payment to treated suppliers

VARIABLES	(1) OLS	(2) Fixed effects	(3) Fixed effects
Treated x Post	3.637*** (0.211)	2.051*** (0.274)	2.050*** (0.274)
FCSupCust x Post			-0.00541 (0.0562)
Observations	109,441	109,441	109,441
R-squared	0.004	0.537	0.537
Controls	NO	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: This table displays the results of estimating equation 30. Fixed effect columns include supplier x customer fixed effects and year dummies.

Next, Table 15 examines the parallel trends assumption. The pre-period shows that the difference between treated and untreated pairs was becoming less positive, while the post-period shows that the difference becomes more positive. The fact that the pre and post period trends go in opposite direction confirms that there was no pre-existing force that was already increasing the gap between treated and untreated pairs. However, the fact that there was some trend in the difference in the pre-period calls into question if there was an omitted factor responsible for both pre and post period trends.

VARIABLES	(1) OLS	(2) OLS
Treated x 2010	4.983*** (0.323)	3.927*** (0.352)
Treated x 2011	0.481** (0.197)	0.678*** (0.208)
Treated x 2012	0.960*** (0.225)	1.029*** (0.240)
Treated x 2013	7.521*** (0.367)	7.628*** (0.382)
FCSupCust		-0.708*** (0.0396)
FCSupCust x Post		-0.106* (0.0582)
Observations	109,441	109,441
R-squared	0.010	0.015

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: This table displays the results of estimating equation 30 with a vector of time dummies to replace the *Post* dummy. Fixed effect columns include supplier x customer fixed effects and year dummies.

To see if the treatment effect can be explained by traditional theory, I explore the role of financial constraints in driving the treatment effect. The traditional theory predicts that suppliers should have a higher propensity to pass the extra funding from the government's accelerated payment to its other customers when the customer values the

funding more than the supplier. This means that the treatment effect should be strongest when the supplier's financial constraints are weak relative to the customer's.

To test these predictions, I split the sample into four groups of supplier-customer pairs based on high versus low customer financial constraints and high versus low supplier financial constraints and estimate treatment effects for each group. Equation 31 modifies equation 30 to include four treatment variables to instead of one

$$DBT_{c,s,t} = \beta_0 + \beta Treated_s \cdot Post_t \cdot FC_{c,s} + \theta Z + \psi_t + \alpha_{c,s} + \epsilon_{c,s,t} \quad (31)$$

where $Treated_s \cdot Post_t$ is interacted with a vector of dummy variables, FC that indicate the supplier-customer pair's financial constraint category. Specifically, FC contains four dummy variables that indicate whether or not the supplier and the customer are financially constrained, $Unconstr.Sup. \cdot Constr.Cust.$, $Constr.Sup. \cdot Constr.Cust.$, $Constr.Sup. \cdot Unconstr.Cust.$, and $Unconstr.Sup. \cdot Unconstr.Cust.$.

Table 16 shows the results from estimating equation 31. Rows 1 and 4 show statistically insignificant coefficients, suggesting that there is no effect for firm pairs with an unconstrained supplier. This suggests that the reform does not change the payment timing trade-off for firm pairs with unconstrained supplier.

Rows 2 and 3 show positive and significant coefficients, suggesting that the treatment effect is concentrated on firm pairs with a constrained supplier. Comparing rows 2 and 3, the coefficient is stronger for firm pairs with an unconstrained customer compared to a constrained customer. This contradicts the traditional theory, which predicts the opposite, that the reform should influence constrained customers, not unconstrained customers, to pay later. However, these results are consistent with the theory in this paper.

VARIABLES	(1) Fixed Effects	(2) Fixed Effects
Unconstr. Sup. x Constr. Cust.	0.0126 (0.875)	-0.188 (0.899)
Constr. Sup. x Constr. Cust.	1.976*** (0.368)	1.936*** (0.371)
Constr. Sup. x Unconstr. Cust.	2.538*** (0.417)	2.625*** (0.424)
Unconstr. Sup. x Unconstr. Cust.	0.458 (1.286)	0.384 (1.288)
FCSupCust x Post		-0.0612 (0.0588)
Observations	109,441	109,441
R-squared	0.537	0.537
Controls	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 16: This table displays the results of estimating equation 31. Fixed effect columns include supplier x customer fixed effects and year dummies.

10.6 Bargaining power results

Next, I explore the role of bargaining power. First, I restrict the sample of customer-supplier pairs to those in which the customer has high bargaining power and estimate equation 30, the baseline specification. I use the binary measure of bargaining power to restrict the sample, where the customer is considered high bargaining power if it is larger than the supplier's average customer.

I restrict the sample to treated customer-supplier pairs and examine the role of bargaining power in driving the treatment effect. The purpose of this exercise is to see if treated suppliers pass more funding to high versus low bargaining power customers. Exploiting variation in treated suppliers' customer base, I look within a treated supplier and compare delinquency from high versus low bargaining power customers before and after the reform. In this sense, I am performing a difference in differences estimation, where the presence of a high bargaining power customer acts as the treatment variable. Specifically, I estimate equation 32

$$DBT_{c,s,t} = \beta_0 + \beta_1 BPCustRival_{c,s,0} \cdot Post_t + \theta Z + \psi_t + \alpha_{c,s} + \epsilon_{c,s,t} \quad (32)$$

β_1 is the difference in differences estimator, which captures the difference in the difference in delinquency between high and low bargaining customers from treated suppliers before and after the reform. Table 17 display the regression results. Columns 1 and 2 show that the difference in differences estimator is positive, though not statistically significant, when using fixed effects regressions. Columns 3 and 4 show that the estimator becomes stronger and statistically significant when using the tobit regression. Since a non-negligible fraction of observations are 0, the tobit left censored regression is more appropriate compared to a linear regression and the change in magnitude and significance is expected. For this reason, I interpret the results as evidence that treated suppliers used the extra funding to allow high bargaining power customers to pay later relative to low bargaining power customers and argue the lack of significance in the fixed effects regressions should not cast doubts on the result.

VARIABLES	(1) Fixed Effects	(2) Fixed Effects
BP x Post	1.454** (0.568)	1.657*** (0.586)
FCSupCust x Post		0.314* (0.180)
Observations	15,463	15,463
R-squared	0.500	0.500
Controls	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: This table displays the results of estimating equation 32. Fixed effect columns include supplier x customer fixed effects and year dummies.

10.7 Product substitutability results

Next, I test the model's predictions on how product substitutability should temper the treatment effect. The model predicts that for high bargaining power customers, the treatment effect should be stronger when product substitutability is low. The model predicts the opposite for low bargaining power customers, that the treatment effect should be stronger when product substitutability is high. I estimate equation on two subsamples, one where customers have bargaining power ($BPCustRival = 1$) and one where customers do not have bargaining power ($BPCustRival = 0$).

$$DBT_{c,s,t} = \beta_0 + \beta_1 Treated \cdot Post_t \cdot Rival_{c,s,0} + \beta_2 Treated \cdot Post_t + \beta_3 Post_t \cdot Rival_{c,s,0} + \theta \mathbf{Z} + \psi_t + \alpha_{c,s} + \epsilon_{c,s,t} \quad (33)$$

Tables 18 and 19 display the results from estimating equation 33, where Table 18 represents firm pairs with a low bargaining customer and Table 19 represents firm pairs with a high bargaining power customer. The coefficient of interest is β_1 . Supporting the model's predictions, the coefficients on β_1 are positive and statistically significant for low bargaining power customers. The coefficients on β_1 are also positive for high bargaining power customers, but are statistically insignificant. While this result does not strongly contradict the model's predictions, it also does not provide evidence in favor of the model's prediction.

VARIABLES	(1) Fixed Effects	(2) Fixed Effects
Rival x Treated x Post	3.934*** (1.283)	3.922*** (1.284)
Rival x Post	-1.230*** (0.414)	-1.212*** (0.419)
Treated x Post	-2.079* (1.165)	-2.071* (1.166)
FCSupCust x Post		-0.0252 (0.101)
Observations	27,685	27,685
R-squared	0.526	0.526

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: This table displays the results of estimating equation 33 for the subsample of low bargaining power customers. Fixed effect columns include supplier x customer fixed effects and year dummies.

VARIABLES	(1) Fixed Effects	(2) Fixed Effects
Rival x Treated x Post	0.877 (0.901)	0.899 (0.900)
Rival x Post	-1.057*** (0.316)	-1.115*** (0.330)
Treated x Post	2.167*** (0.783)	2.160*** (0.782)
FCSupCust x Post		0.0630 (0.0874)
Observations	56,625	56,625
R-squared	0.539	0.539

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: This table displays the results of estimating equation 33 for the subsample of high bargaining power customers. Fixed effect columns include supplier x customer fixed effects and year dummies.

11 Conclusion

I investigate why large financially unconstrained firms delay payment to small financially constrained suppliers. I show theoretically that large firms can use payment delays as a tool to constrain the supplier's ability to fund production for rival customers and therein reduce competition. Empirically, I obtain a new inter-firm credit dataset to test the theory's main predictions on how financial constraints, bargaining power, and product substitutability should determine payment delays. In addition to examining equilibrium relationships, I exploit a government program as an exogenous shock to supplier financial constraints. The empirical results support the theoretical predictions.

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Model Appendix

Proof of equation 13:

The first order condition on τ_2 comes from the optimization problem specified in equation 10, which is reproduced below:

$$\max_{q_2, p_2, \tau_2 \geq 0} \pi_S(\mathbf{x}_1^*, \mathbf{x}_2, b_S^*(\mathbf{x}_1^*, \mathbf{x}_2))$$

Subject to:

$$R_2 \text{ participation constraint: } 0 \leq \pi_{R_2}(\mathbf{x}_2, b_2^*(\mathbf{x}_2))$$

Expanding the profit functions gives equation 34

$$\max_{q_2, p_2, \tau_2 \geq 0} p_1 q_1 + p_2 q_2 - c \cdot (q_1 + q_2) - r_S^* b_S^* \quad (34)$$

Subject to:

$$R_2 \text{ participation constraint: } 0 \leq P_2 q_2 - p_2 q_2 - r_2^* b_2^*$$

I argue that the participation constraint must bind. Intuitively, To see this formally consider that the participation does not bind. The first order condition on p_2 in the unconstrained problem is

$$q_2 - \frac{\partial r_S^* b_S^*}{\partial p_2} = 0 \quad (35)$$

Note that q_2 and $-\frac{\partial r_S^* b_S^*}{\partial p_2}$ are positive. To see the latter, observe that b_S^* is stage 3 equilibrium outcome is the budget constraint, $b_S^* = c \cdot (q_1 + q_2) - [(1 - \tau_1)p_1 q_1 + (1 - \tau_2)p_2 q_2]$. As a result, b_S^* a decreasing function of p_2 , $\frac{\partial b_S^*}{\partial p_2} = -(1 - \tau_2)q_2 < 0$. Using this derivative we see that $\frac{\partial r_S^* b_S^*}{\partial p_2} = \frac{\partial \theta_S(b_S^*)^2}{\partial p_2} = 2\theta_S b_S^* \frac{\partial b_S^*}{\partial p_2}$ is also negative, rendering $-\frac{\partial r_S^* b_S^*}{\partial p_2}$ positive. Since both q_2 and $\frac{\partial r_S^* b_S^*}{\partial p_2}$ are positive, the left side of this equation will always be greater than the right. Accordingly, it would be optimal to increase p_2 infinitely. However, an infinite p_2 will not satisfy the participation constraint as R_2 's profit function is decreasing in p_2 and would drop below 0 if p_2 were infinite.

Moving on, the Lagrangian for the constrained optimization problem is

$$\max_{q_2, p_2, \tau_2 \geq 0} p_1 q_1 + p_2 q_2 - c \cdot (q_1 + q_2) - r_S^* b_S^* - \lambda_2 (P_2 q_2 - p_2 q_2 - r_2^* b_2^*) \quad (36)$$

The first order condition on τ_2 is

$$-\frac{\partial r_S^* b_S^*}{\partial \tau_2} + \lambda_2 \frac{\partial r_2^* b_2^*}{\partial \tau_2} = 0 \quad (37)$$

Note that since the only two places where τ_2 appears are in the financing costs, these are the only two terms in the expression. Next, I argue that $\lambda_2 = 1$. It is standard in Nash bargaining over vertical supply contracts that the optimal contract is the one that maximizes the joint profits and the price implements a transfer between the two parties according to the share parameters. Intuitively, relaxing the participation constraint by a dollar would allow the supplier to extract an extra dollar of the joint profit while still satisfying the participation constraint. Further, as a check, the Matlab analytical solver found a multiplier value of 1.

Proof of equation 14:

The first order condition on τ_1 comes from the optimization problem specified in equation 12 and is reproduced below:

$$\max_{q_1, p_1, \tau_1 \geq 0} \pi_{R_1}(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1), b_1^*(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1)))$$

Subject to:

$$S \text{ participation constraint: } 0 \leq \pi_S(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1), b_S^*(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1))) - \pi_{S_1}^D$$

Expanding the profit functions gives equation 38

$$\max_{q_1, p_1, \tau_1 \geq 0} P_1 q_1 - p_1 q_1 - r_1^* b_1^* \quad (38)$$

Subject to:

$$S \text{ participation constraint: } 0 \leq p_1 q_1 + p_2^* q_2^* - c \cdot (q_1^* + q_2^*) - r_S^* b_S^* - \pi_{S_1}^D$$

Note that the small retailer's equilibrium contract in stage 2 is a function of the large retailer's contract in stage 1. Similarly, the equilibrium loan sizes in stage 3 are functions of the small and large retailer's contracts in stages 1 and 2. For notational simplicity, I do not explicitly writing these as functions. However, to be clear, the equilibrium objects in equation 38 are functions of the equilibrium outcomes in prior stages. For example, p_2^* represents the function $p_2^*(\mathbf{x}_1)$ and b_S^* represents the function $b_S^*(\mathbf{x}_1, \mathbf{x}_2^*(\mathbf{x}_1))$.

By the same logic as in the proof behind equation 13, the participation constraint binds. The Lagrangian for the constrained optimization problem is

$$\max_{q_1, p_1, \tau_1 \geq 0} P_1 q_1 - p_1 q_1 - r_1^* b_1^* - \lambda_1 (p_1 q_1 + p_2^* q_2^* - c \cdot (q_1 + q_2^*) - r_S^* b_S^* - \pi_{S_1}^D) \quad (39)$$

For ease of exposition, I transform the Lagrangian with one extra step. I add R_2 's participation constraint to the supplier's. Since I already proved that R_2 's participation constraint is 0, adding 0 to the Lagrangian leaves it unchanged.

$$\max_{q_1, p_1, \tau_1 \geq 0} P_1 q_1 - p_1 q_1 - r_1^* b_1^* + \lambda_1 (p_1 q_1 - c \cdot (q_1 + q_2^*) - r_S^* b_S^* + P_2^* q_2^* - r_2^* b_2^* - \pi_{S_1}^D) \quad (40)$$

The first order condition on τ_1 is

$$\frac{\partial P_1^* q_1^*}{\partial \tau_1} - \frac{\partial r_1^* b_1^*}{\partial \tau_1} - \lambda_1 \left(\frac{\partial r_S^* b_S^*}{\partial \tau_1} - \frac{\partial (P_2^* - c) q_2^*}{\partial \tau_1} \right) = 0 \quad (41)$$

By the same logic as in the proof behind equation 13, the multiplier is 1, so $\lambda_1 = 1$. Rearranging this equation gives equation 14.

Proof of equation 18:

This goal is to derive equation 18 from equation 17. For reference, equation 17 is:

$$\underbrace{\frac{\partial r_S^* b_S^*}{\partial \tau_1} + \frac{\partial r_2^* b_2^*}{\partial \tau_1} - \left(\frac{\partial P_2^* q_2^*}{\partial \tau_1} - \frac{\partial c q_2^*}{\partial \tau_1} \right)}_{\text{Marginal cost}} = \underbrace{\frac{\partial P_1^* q_1^*}{\partial \tau_1}}_{\text{Marginal benefit}}$$

R_2 and S have equilibrium loan sizes of:

$$b_S^* = \theta_2 \frac{2q_1^* (c - (1 - \tau_1^*) p_1^*) + c(1 - \epsilon q_1^* - c)}{2(c^2 \theta_S \theta_2 + \theta_S + \theta_2)} \quad (42)$$

$$b_2^* = \theta_S \frac{2q_1^* (c - (1 - \tau_1^*) p_1^*) + c(1 - \epsilon q_1^* - c)}{2(c^2 \theta_S \theta_2 + \theta_S + \theta_2)} \quad (43)$$

Using equations 42 and 43, the derivative of $r_S^* b_S^* + r_2^* b_2^*$ with respect to τ_1 is:

$$\frac{\partial r_S^* b_S^*}{\partial \tau_1} + \frac{\partial r_2^* b_2^*}{\partial \tau_1} = 2\theta_S b_S^* \frac{\partial b_S^*}{\partial \tau_1} + 2\theta_2 b_2^* \frac{\partial b_2^*}{\partial \tau_1} = 2(b_S^* + b_2^*) \frac{\theta_S \theta_2 p_1^* q_1^*}{c^2 \theta_S \theta_2 + \theta_S + \theta_2} \quad (44)$$

Next, I reduce expression from 44. First note that R_2 's equilibrium quantity is:

$$q_2^* = \frac{-2c\theta_S \theta_2 q_1^* (c - (1 - \tau_1^*) p_1^*) + (1 - \epsilon q_1^* - c)(\theta_2 + \theta_S)}{2(c^2 \theta_S \theta_2 + \theta_S + \theta_2)} \quad (45)$$

Differentiating q_2^* with respect to τ_1 gives:

$$\frac{dq_2^*}{d\tau_1} = -c \cdot \frac{\theta_S \theta_2 p_1^* q_1^*}{c^2 \theta_S \theta_2 + \theta_S + \theta_2} \quad (46)$$

Putting equation 44 in terms of $\frac{dq_2^*}{d\tau_1}$ gives:

$$\frac{\partial r_S^* b_S^*}{\partial \tau_1} + \frac{\partial r_2^* b_2^*}{\partial \tau_1} = -\frac{2}{c}(b_S^* + b_2^*) \frac{dq_2^*}{d\tau_1}$$

Replacing the expression for $\frac{\partial r_S^* b_S^*}{\partial \tau_1} + \frac{\partial r_2^* b_2^*}{\partial \tau_1}$ in equation 17 gives the desired result.

Proof that τ_1 is unique:

The first order condition on τ_1 is given in equation 18 reproduced below. To show that the equilibrium τ_1 , I will show that the marginal cost side is strictly increasing in τ_1 and marginal benefit side is constant in τ_1 .

$$\underbrace{\frac{2}{c}(b_S^* + b_2^*) \frac{\partial q_2^*}{\partial \tau_1}}_{\text{Financing costs}} + \underbrace{(P_2^* - q_2^* - c) \frac{\partial q_2^*}{\partial \tau_1}}_{\text{Output effect}} = \underbrace{\epsilon q_1^* \frac{\partial q_2^*}{\partial \tau_1}}_{\text{Competition effect}}$$

Marginal cost Marginal benefit

To show that the marginal cost side is strictly increasing in τ_1 , I show that b_S^* and b_2^* are strictly increasing in τ_1 and q_2^* is strictly decreasing in τ_1 . Using equations 46 and 44, I reproduce the derivatives of these variables with respect to τ_1 .

$$\frac{dq_2^*}{d\tau_1} = -c \cdot \frac{\theta_S \theta_2 p_1^* q_1^*}{c^2 \theta_S \theta_2 + \theta_S + \theta_2} < 0$$

$$\frac{db_S^*}{d\tau_1} = -\frac{2}{c} b_S^* \frac{dq_2^*}{d\tau_1} < 0$$

$$\frac{db_2^*}{d\tau_1} = -\frac{2}{c} b_2^* \frac{dq_2^*}{d\tau_1} < 0$$

Lastly, in order to ensure that both sides of the equation do not both equal zero, we need the condition that $\frac{\partial q_2^*}{\partial \tau_1} \neq 0$. This comes from the assumptions that $\theta_2 > 0$ and $\theta_S > 0$.

Figures Appendix

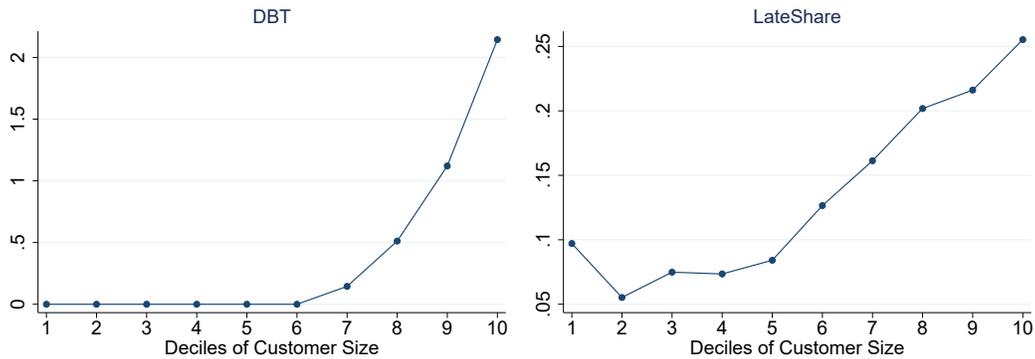


Figure 19: This figure plots the median delinquency over deciles of customer size. Customer size is measured by the customer's employee size category. The left panel measures delinquency using *DBT*, while the right panel measures delinquency using *LateShare*.

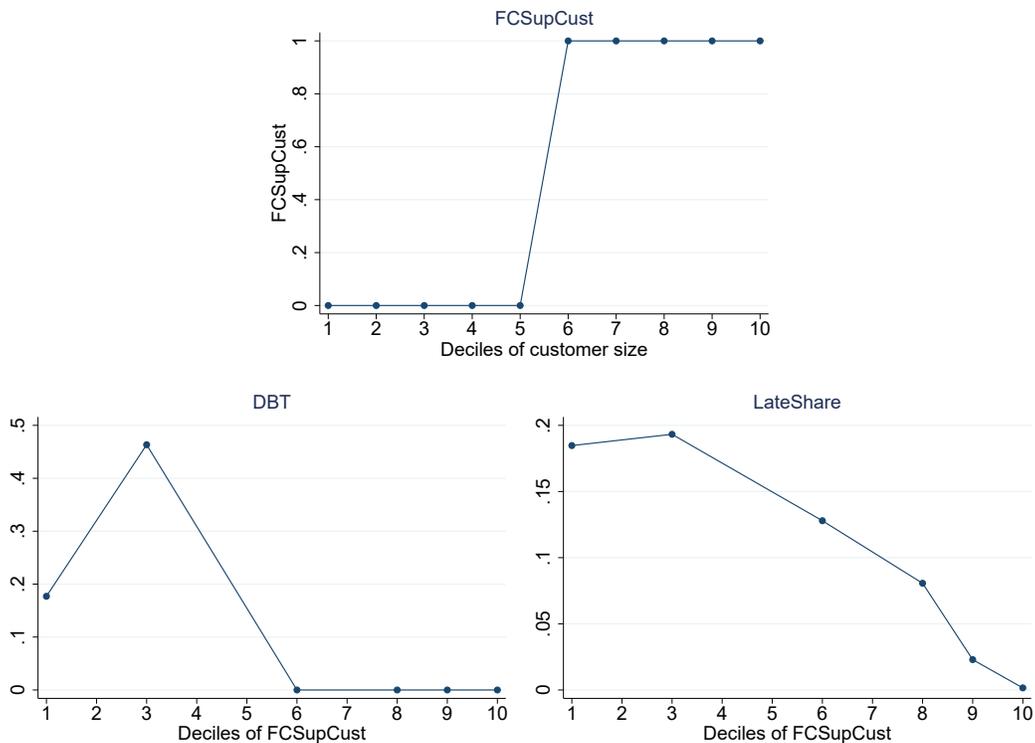


Figure 20: The top panel of this figure plots the median relative financial constraints over deciles of customer size. The bottom panels plot the median delinquency over deciles of relative financial constraints. Relative financial constraints are measured using *FCSupCust*. The bottom left panel measures delinquency using *DBT*, while the bottom right panel measures delinquency using *LateShare*.

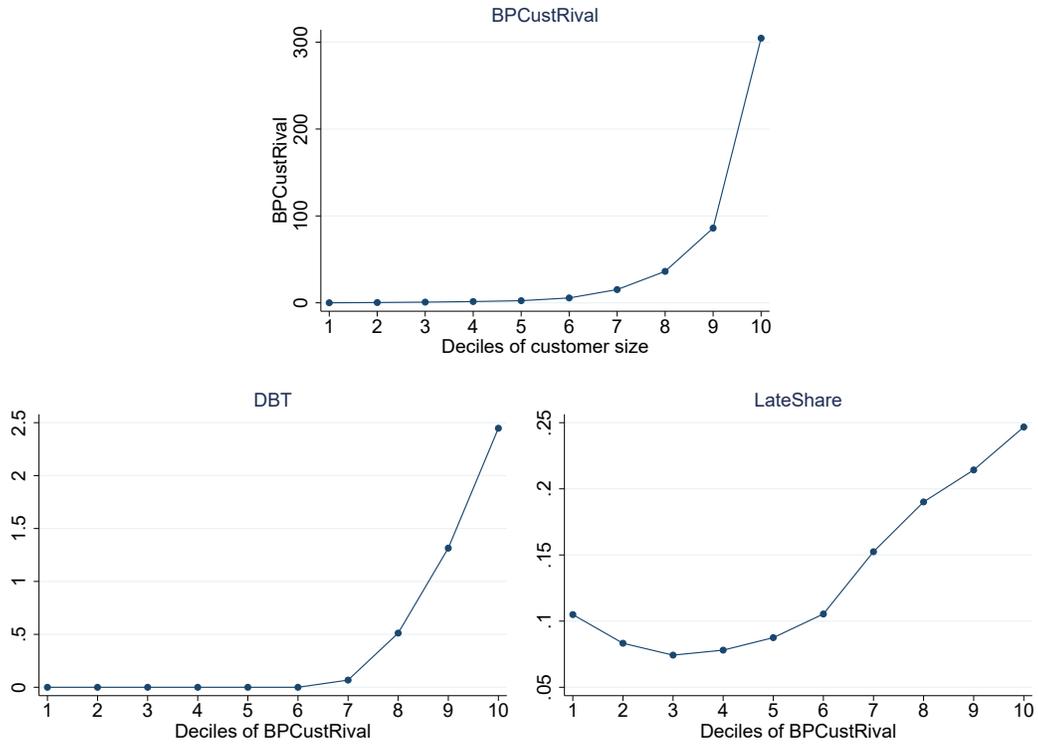


Figure 21: The top panel of this figure plots the median bargaining power over deciles of customer size. The bottom panels plot median delinquency over deciles of bargaining power. The bottom left panel measures delinquency using *DBT*, while the bottom right panel measures delinquency using *LateShare*. Bargaining power is measured using the continuous version of *BPCustRival*.

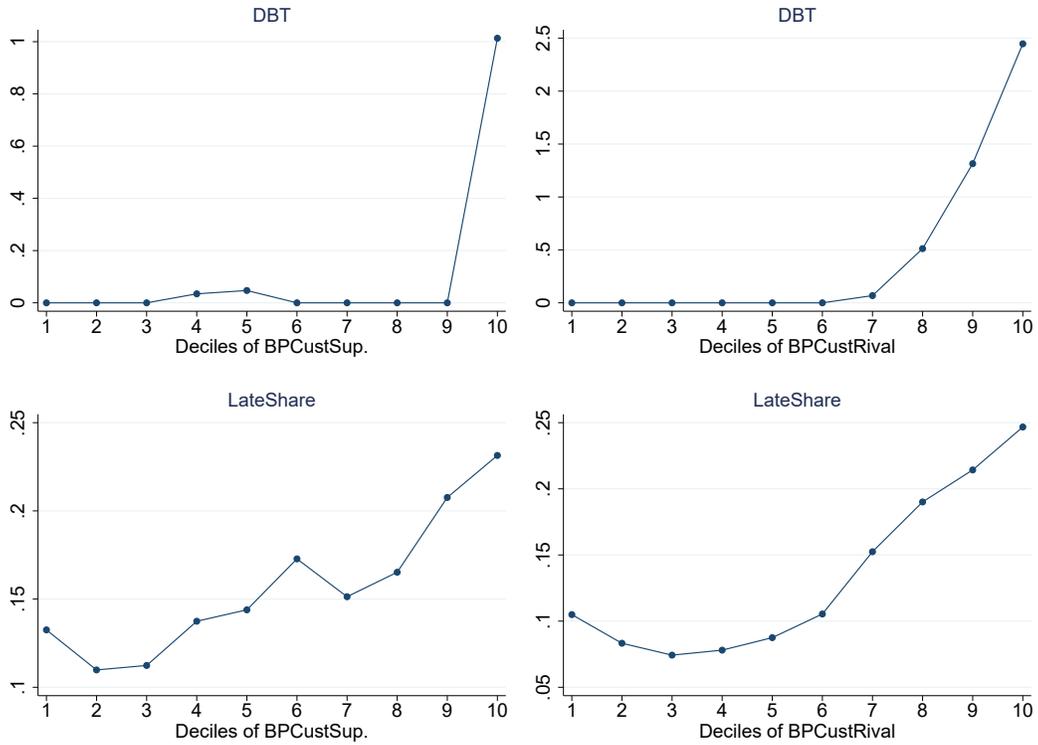


Figure 22: This figure plots the median delinquency over deciles of bargaining power. Delinquency is measured using *DBT* in the top panels and *LateShare* in the bottom panels. Bargaining power is measured using *BPCustSup* in the left panel and *BPCustRival* in the right panels.

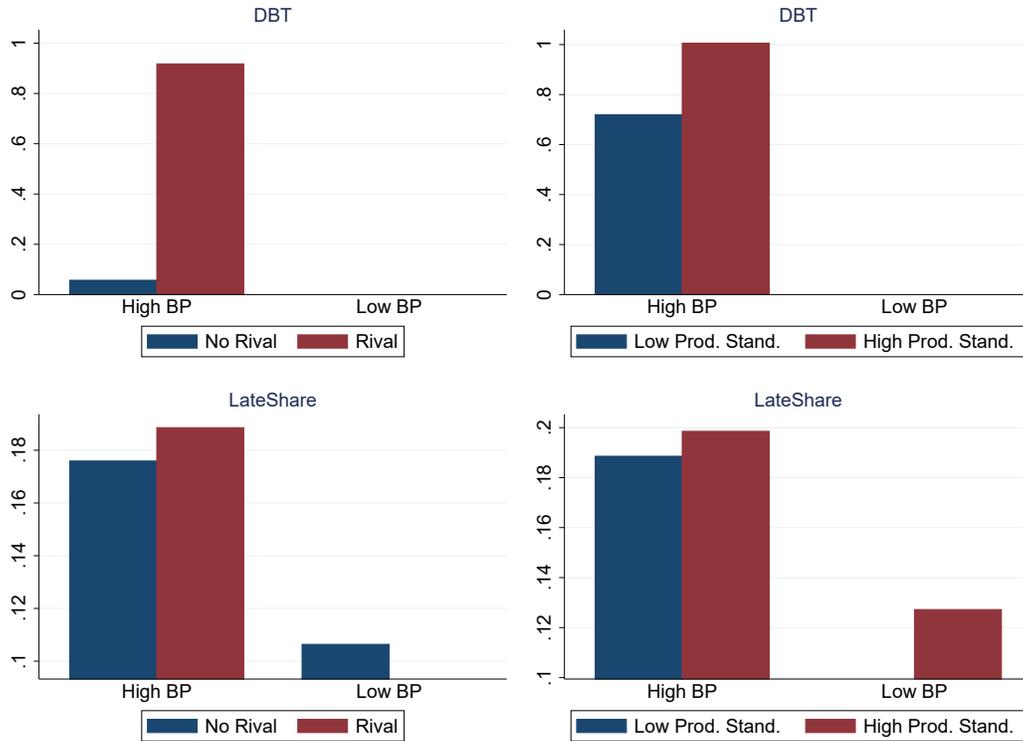


Figure 23: This figure plots the median delinquency by product substitutability and bargaining power. In each panel, the left bars contain customer-supplier pairs with a high bargaining power customer, while right bars do not. Blue bars represent low product substitutability, while red columns represent high product substitutability. Delinquency is measured using *DBT* in the top panels and *LateShare* in the bottom panels. Product substitutability is measured using *Rival* in the left column and *Prod. Stand.* in the right column. Bargaining power is measured using *BPCustRival*.

Tables Appendix

Appendix A

In this appendix, I show robustness of equilibrium relationships to alternative specifications of fixed effects. I reproduce the results of section 9 under two alternative specifications of fixed effects. The first is a combination of customer x supplier and time fixed effects and the second is a combination of customer x time and supplier fixed effects.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects
BPCustRival100			1.250** (0.564)
BPCustRival	-0.667*** (0.179)	-0.856** (0.359)	-0.514 (0.377)
FCSupCust	82.47*** (23.48)	0.815 (2.946)	0.413 (2.940)
FCRival	-96.04*** (27.40)	-5.962** (3.025)	-5.750* (3.018)
Observations	153,410	71,223	71,169
R-squared	0.238	0.207	0.207
Controls	NO	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 20: This table examines the effect of bargaining power on *DBT*. The results are obtained by estimating equation 26. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by customer x time and supplier fixed effects.

VARIABLES	(1) Fixed effects	(2) Fixed effects
Cust. Size x BPCustRival	-0.614*** (0.190)	-0.584* (0.322)
Cust. Size x BPCustRival100		0.152 (0.444)
BPCustRival	2.396** (0.962)	2.681 (1.800)
BPCustRival100		-0.248 (4.659)
FCSupCust	82.64*** (23.49)	0.451 (2.934)
FCRival	-96.16*** (27.41)	-5.749* (3.019)
Observations	153,410	71,169
R-squared	0.238	0.207
Controls	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 21: This table examines the effect of customer size on *DBT* across different levels of bargaining power. The results are obtained by estimating equation 26 with an interaction effect between bargaining power and customer size. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by customer x time and supplier fixed effects.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects
BPCustRival		0.384*** (0.135)	0.292 (0.314)
BPCustSup	2.247*** (0.166)	1.008*** (0.186)	1.497*** (0.311)
FCSupCust		-1.313*** (0.0469)	-1.245*** (0.0863)
Cust. Book Lev.			1.994*** (0.483)
Cust. Cash/Assets			0.187 (0.580)
Observations	71,933	71,933	35,461
R-squared	0.114	0.123	0.138
Sup. x Cust. Ind x Year FE	YES	YES	YES
Controls	NO	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 22: This table compares the effects of two different bargaining power measures on *DBT*. The results are obtained by estimating equation 27. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by customer x time and supplier fixed effects.

Appendix B

In this appendix, I show robustness of equilibrium relationships to using the *LateShare* measure. To do so, I reproduce the results of section 9 using the *LateShare* measure as the dependent variable.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Tobit	(4) Tobit
FCSupCust	-0.0298*** (0.000819)	-0.0219*** (0.00181)	-0.0236*** (0.00103)	-0.0102*** (0.00149)
Cust. Book Lev.		0.0454*** (0.00888)		0.0181*** (0.00668)
Cust. Cash/Assets		-0.0422*** (0.0109)		-0.0375*** (0.00909)
FCRival			0.155*** (0.00650)	0.115*** (0.00932)
Observations	193,464	90,238	202,134	90,238
R-squared	0.615	0.712		
Controls	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: This table examines the effect of financial constraints on *LateShare*. The results are obtained by estimating equation 26, excluding the *BPCustRival* explanatory variable. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Tobit	(4) Tobit	(5) Fixed effects	(6) Tobit
BPCustRival100					0.0494*** (0.00610)	0.0718*** (0.00590)
BPCustRival	-0.00118 (0.00273)	0.00438 (0.00693)	0.0529*** (0.00378)	0.0242*** (0.00715)	-0.00192 (0.00696)	0.00976 (0.00722)
FCSupCust	-0.0297*** (0.000981)	-0.0213*** (0.00215)	-0.0227*** (0.00118)	-0.0101*** (0.00170)	-0.0188*** (0.00216)	-0.00633*** (0.00172)
Cust. Book Lev.		0.0440*** (0.0103)		0.0177** (0.00725)	0.0394*** (0.0102)	0.0144** (0.00725)
Cust. Cash/Assets		-0.0398*** (0.0127)		-0.0292*** (0.0102)	-0.0336*** (0.0127)	-0.0220** (0.0102)
FCRival			0.170*** (0.00751)	0.129*** (0.0107)		0.142*** (0.0107)
Observations	149,624	72,658	156,020	72,658	72,604	72,604
R-squared	0.645	0.736			0.737	
Controls	NO	YES	NO	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: This table examines the effect of bargaining power on *LateShare*. The results are obtained by estimating equation 26. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Tobit	(4) Tobit	(5) Fixed effects	(6) Tobit
BPCustRival100					0.0494*** (0.00610)	0.0718** (0.00590)
BPCustRival	-0.00118 (0.00273)	0.00438 (0.00693)	0.0529*** (0.00378)	0.0242*** (0.00715)	-0.00192 (0.00696)	0.00976 (0.00722)
FCSupCust	-0.0297*** (0.000981)	-0.0213*** (0.00215)	-0.0227*** (0.00118)	-0.0101*** (0.00170)	-0.0188*** (0.00216)	-0.00633 (0.00172)
Cust. Book Lev.		0.0440*** (0.0103)		0.0177** (0.00725)	0.0394*** (0.0102)	0.0144** (0.00725)
Cust. Cash/Assets		-0.0398*** (0.0127)		-0.0292*** (0.0102)	-0.0336*** (0.0127)	-0.0220* (0.0102)
FCRival			0.170*** (0.00751)	0.129*** (0.0107)		0.142*** (0.0107)
Observations	149,624	72,658	156,020	72,658	72,604	72,604
R-squared	0.645	0.736			0.737	
Controls	NO	YES	NO	YES	YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 25: This table examines the effect of bargaining power on *DBT* for customer-supplier firms with a financially unconstrained customer. A financially unconstrained customer is defined as a customer firm with a risk class of 3 or lower. The results are obtained by estimating equation 26 on this subsample. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

VARIABLES	(1) Fixed effects	(2) Tobit	(3) Fixed effects	(4) Tobit
Cust. Size	-0.00964*** (0.00168)	-0.0105*** (0.00208)	-0.00837** (0.00424)	-0.00263 (0.00377)
Cust. Size x BPCustRival	0.0232*** (0.00182)	0.0350*** (0.00230)	0.0215*** (0.00460)	0.0185*** (0.00424)
Cust. Size x BPCustRival100			-0.00517 (0.00557)	0.00416 (0.00554)
BPCustRival	-0.122*** (0.00774)	-0.165*** (0.0110)	-0.121*** (0.0205)	-0.119*** (0.0217)
BPCustRival100			0.0665 (0.0546)	-0.0130 (0.0563)
FCSupCust	-0.0261*** (0.00100)	-0.0175*** (0.00119)	-0.0170*** (0.00218)	-0.00460*** (0.00173)
Cust. Book Lev.			0.0370*** (0.0102)	0.0119 (0.00726)
Cust. Cash/Assets			-0.0224* (0.0128)	-0.0141 (0.0102)
FCRival		0.133*** (0.00776)		0.113*** (0.0114)
Observations	149,624	156,020	72,604	72,604
R-squared	0.647		0.738	
Controls	NO	NO	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: This table examines the effect of customer size on *LateShare* across different levels of bargaining power. The results are obtained by estimating equation 26 with an interaction effect between bargaining power and customer size. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

VARIABLES	(1) Fixed effects	(2) Fixed effects	(3) Fixed effects	(4) Tobit	(5) Tobit
BPCustRival100			0.0199 (0.0155)		0.0399*** (0.00900)
BPCustRival		-0.0137 (0.0152)	-0.0142 (0.0152)	-0.00708 (0.0108)	-0.0129 (0.0109)
BPCustSup	0.0408*** (0.00852)	0.0273 (0.0184)	0.0164 (0.0200)	0.0574*** (0.00785)	0.0496*** (0.00804)
FCSupCust		-0.0153*** (0.00489)	-0.0146*** (0.00494)	0.00636** (0.00252)	0.00740*** (0.00253)
Cust. Book Lev.		0.0441** (0.0222)	0.0430* (0.0222)		
Cust. Cash/Assets		-0.0402 (0.0316)	-0.0394 (0.0316)		
FCRival				0.0887*** (0.0170)	0.0928*** (0.0171)
Observations	78,400	36,259	36,225	36,259	36,225
R-squared	0.707	0.764	0.764		
Controls	NO	YES	YES	NO	NO

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 27: This table compares the effects of two different bargaining power measures on *LateShare*. The results are obtained by estimating equation 27. Fixed effect columns represent fixed effects regressions, where fixed effects are defined by supplier x customer 4 digit SIC industry x time. Tobit columns represent tobit random effects regressions with year dummies.

VARIABLES	(1) SIC4 Rival	(2) SIC4 Rival	(3) No Rival	(4) No Rival	(5) StandInd	(6) StandInd	(7) DiffInd	(8) DiffInd
BPCustRival100		0.0688*** (0.00711)		0.0824*** (0.00948)		0.0948*** (0.0137)		0.0618*** (0.0071)
BPCustRival	0.0195** (0.00797)	0.00711 (0.00804)	0.0259* (0.0140)	0.00417 (0.0141)	-0.0157 (0.0153)	-0.0312** (0.0154)	0.0170* (0.00962)	0.00317 (0.0097)
FCSupCust	-0.0216*** (0.00213)	-0.0184*** (0.00215)	0.00230 (0.00273)	0.00662** (0.00276)	-0.00611 (0.00400)	-0.000122 (0.00406)	-0.00842*** (0.00213)	-0.0046 (0.0021)
FCRival	0.195*** (0.0144)	0.209*** (0.0144)	0.0929*** (0.0160)	0.108*** (0.0160)	0.156*** (0.0244)	0.177*** (0.0244)	0.0784*** (0.0131)	0.0893*** (0.0132)
Cust. Book Lev.	0.0137* (0.00794)	0.00996 (0.00794)	0.0255 (0.0159)	0.0222 (0.0159)	0.0222 (0.0150)	0.0201 (0.0150)	0.0123 (0.00977)	0.00893 (0.0097)
Cust. Cash/Assets	-0.0332*** (0.0108)	-0.0262** (0.0108)	-0.0322 (0.0259)	-0.0274 (0.0258)	-0.0753*** (0.0205)	-0.0643*** (0.0204)	-0.0179 (0.0137)	-0.0104 (0.0137)
Observations	48,143	48,135	24,515	24,469	13,524	13,512	45,778	45,748

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 28: This table examines the effect of bargaining power on *LateShare* across subsamples with different levels of product substitutability. The results are obtained by estimating equation 28. All specifications are tobit random effects regressions with year dummies. Column (1) restricts the sample to customer-supplier pairs where the supplier has another customer in the same 4 digit SIC industry as the customer. Column (2) restricts the sample to customer-supplier pairs where the supplier does not have another customer in the same 4 digit SIC industry as the customer. Column (3) restricts the sample to customer-supplier pairs where the customer's industry is considered standardized by the Racuh (1999) classification. Column (4) restricts the sample to customer-supplier pairs where the customer's industry is not considered standardized by the Racuh (1999) classification.

VARIABLES	(1) High BP	(2) High BP	(3) High BP	(4) BP	(5) BP	(6) BP	(7) No BP	(8) No BP
StandInd	0.0154 (0.0126)			-0.0166** (0.00657)			0.00370 (0.0178)	
Rival (SIC4)		0.0239*** (0.00771)			0.0252*** (0.00431)			0.0239*** (0.00771)
# Rivals (SIC4)			-0.000611** (0.000311)			-0.000712*** (0.000130)		-0.000611** (0.000311)
FCSupCust	0.0118*** (0.00399)	0.00661* (0.00369)	0.00936** (0.00366)	-0.00681*** (0.00198)	-0.0105*** (0.00183)	-0.00761*** (0.00182)	-0.0185*** (0.00586)	-0.00681*** (0.00198)
FCRival	0.114*** (0.0234)	0.143*** (0.0223)	0.120*** (0.0228)	0.0944*** (0.0121)	0.137*** (0.0114)	0.109*** (0.0116)	0.108*** (0.0376)	0.114*** (0.0234)
Cust. Book Lev.		-0.0104 (0.0212)	-0.00689 (0.0212)		0.0292*** (0.00993)	0.0319*** (0.00994)		-0.0104 (0.0212)
Cust. Cash/Assets		0.0131 (0.0319)	0.0276 (0.0321)		-0.0276** (0.0121)	-0.00643 (0.0124)		0.0131 (0.0319)
Observations	14,741	16,983	16,983	53,247	64,475	64,475	6,055	8,188
Controls	NO	YES	YES	NO	YES	YES	NO	YES

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 29: This table examines the effect of product substitutability on *LateShare* across subsamples with different levels of bargaining power. The results are obtained by estimating equation 29. All specifications are tobit random effects regressions with year dummies. High BP columns restrict the sample to firm pairs where *BPCustRival*100 equals 1. BP columns restrict the sample to firm pairs where *BPCustRival* equals 1. No BP columns restrict the sample to firm pairs where *BPCustRival* equals 0.