Measuring Financial Restrictions of Brazilian Private Firms with Microdata: A Contract Theory Approach

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Abstract

This study develops original measures of financial constraints for a sample of 6,215 private firms in Brazil spanning the period from 2012 to 2022. To construct these metrics, we utilize a granular dataset comprising 11,967,603 loan contracts between these firms and financial institutions, sourced from Banco Central do Brasil's Credit Information System (SCR). Following the theoretical framework of Bester (1985), our identification strategy is based on relative interest rates and collateral requirements within the credit agreements. Using these constraints, we estimate the firms' investment demand and provide empirical evidence that financial frictions exert a statistically significant negative effect on capital expenditure. To provide a structural interpretation of our findings, we calibrate a continuous-time partial equilibrium dynamic stochastic model of investment. The simulation results demonstrate that financial restrictions adversely impact investment by reducing the total factor productivity of private firms.

Keywords: financial restrictions measures, investment, private firms, loans, interest rates, collaterals, System of Credit Register, Banco Central do Brasil

JEL: G13, G32, G38

1. Introduction

Financial restrictions are a key and widespread concern for firms, thwarting their ability to conduct their optimal investment policies and growth trajectories. They are important in academia and well as for policy makers. In the case of the former, they are relevant both in theoretical and empirical work related to large strands of Economics and Finance Literature. In the case of the latter, they are relevant to have an idea of the stance of the credit market in the economy.

The existing theoretical literature on the effect of financing constraints on firms' performance is very extensive. However, empirical contributions are scarce and more recent. In addition, despite its enormous importance, measuring financial restrictions is still subject to much discussion, because most empirical studies have not only to deal with a set of measurement and conceptual issues, but also rely on tenuous relationships between firms and financial institutions to identify the presence and severity of financial constraints.

The very definition of financial restrictions is not clear-cut. One can address several aspects of the relationship between firms and financial institutions to extract measures of financial restrictions.[1] One common feature of all financial restriction measures, however, is the one that differentiates them from financial distress measures. A firm can be healthy and efficient in economic and financial terms, therefore not in distress, and still be credit restricted for some reasons.

In this paper, to measure financial restrictions, we will follow an identification strategy, related to Contract Theory, based on Bester(1985). The author shows that no credit rationing will occur in equilibrium if banks compete by choosing collateral requirements and rates of interest rate screen investors ´riskiness.[2] A credit rationing equilibrium will be characterized by separation of borrowers with low probability of default -less likely to be financially restricted- from borrowers with high probability of default -more likely to be financially restricted. The

[1] Kaplan and Zingales (1997) use a broader definition by stating that financial constraints are present whenever there is a wedge between the costs of obtaining internal and external funds. However, the problem with such definition is that it almost covers every firm.

[2] There is evidence that credit market in Brazil, despite being concentrated on a few financial institutions, is competitive. See Nakane (2002) and Tabak et al. (2015).

latter will choose contracts with a higher interest rate and lower collateral than borrowers with low probability of default.

Therefore, interest rates and collaterals serve as screening mechanisms financial institutions use to separate good from bad borrowers. As Stiglitz and Weiss (1981) indicate, the adverse selection aspect of interest rate is a consequence of different borrowers having different probabilities of repaying their loan. Bester (1985) points out that collaterals may also serve to reveal information about the default risk of loan applicants and that in an equilibrium, the level of collateralization is negatively related to the riskiness of the borrowers´ investment projects.

Our main objective in this paper is to create financial restriction measures of Brazilian private firms (hereafter firms), based on microdata related to financial institutions loan contracts written with these firms and study how or if they affect their investment demand. We look at 11,967,603 loan contracts written between 6,215 private firms (hereafter firms) and financial institutions in this period. These loan contracts come from the System of Credit Register (hereafter SCR) of Banco Central do Brasil (hereafter BCB) from 2012 to 2022. The main idea, as we stress above, comes from Bester (1985), and it is to sort out firms that are considered more likely to be financially restricted by looking at relative levels of interest rates and collateral they agreed on with financial institutions in our sample period.

A problem with the identification strategy mentioned above is that, for some reason, financial institutions may have, for a certain time, observed credit policies that differ from what would be their optimal ones. Just to exemplify, in Brazil some government financial institutions have, in recent past, due political reasons, been softer in giving credit thus having a different behavior towards loan supply from those of financial institutions in the same period. This could have an impact on our capacity to identify in an accurate way borrowers with different levels of riskiness.[3]

To avoid such problems, we adopt Bellucci et al. (2021) and estimate Three Stage Least Square Model (hereafter 3SLS) for every year of our sample period with interest rate and collateral of private firms as dependent variables and several characteristics of financial

[3] See Joaquim et al. (2023) for a case study of Brazil´s government intervention in its most important commercial banks to increase credit in Brazil´s economy.

institutions, private firms, and loans as exogenous or instrumental variables. The idea is to obtain interest rates and collateral series that could mirror better optimal credit policies of financial institutions.

Thus, to measure financial restrictions, we compare, in every year of our sample period, the minimum interest rate and the maximum collateral of each private firms, respectively with benchmark quantiles of the predicted distribution of interest rates and collaterals obtained with 3SLS estimations mentioned above.

With our definitions, we identify a maximum of 1,215 (19.55%) in 2020 and a minimum of 101 (1.63%) in 2012 of firms that are financially restricted. In every year, most of these firms come from the services or industrial sectors. The agricultural sector is the one with fewer firms financially restricted firms in our sample period. We observe that firms that we select as financially restricted are the ones with few loans' contracts written, the great majority of which are working capital loans. Most of them (but not all) are young and small firms. They have mostly short-term relationships with financial institutions. They use mostly internal resources to invest, and financial institutions consider great majority of loans written with these firms very risky.

We perform two different sets of exercises. In the first, we follow Gala et al. (2020) and estimate investment demand for firms without using Q of Tobin. We find that financial restrictions are negatively related to investment for financially restricted firms. In a second set of exercises, we simulate a partial equilibrium stochastic dynamic control model of investment demand and show that financial restrictions, by having a negative impact on productivity, lead firms - which are financially restricted- to invest less relative to those that are more likely to be non-financially restricted firms.

To understand how our measures of financial restrictions contribute to empirical literature, it is important to describe very briefly the current state of the art of empirical literature on this issue. As Silva and Carreira (2012) point out, there are three types of financial restriction measures: indirect measures, direct measures, and indexes.[4] Indirect measures look at the

[4] All types of financially restricted measures can be criticized because of endogeneity arguments. The measures thar empirical literature considers more exogenous and that, because of this, are used more often are size and

sensitivity of investment in relation to cash-flow, and they use average Q of Tobin as a proxy for marginal q of Tobin. Direct measures of financial restrictions, different from indirect measures, do not use average Q of Tobin. They are based on surveys and reports of firms. They are firm specific, time varying, and a researcher can use them as dependent or independent variable in their studies. The third type of measure of financial restrictions is an index. This is a combination of direct and indirect measures. Kaplan and Zingales (997) and Whited and Wu (2006) are some of the most important indexes in literature. They have qualitative and quantitative information and share the advantages and disadvantages of direct and indirect measures. [5] All these measures have important drawbacks that make them imprecise.[6]

Different from what we see in empirical literature and that we draw attention to above, our methodology, by using microdata coming from loan contracts of SCR, allows us to have a better understanding of credit access for firms. SCR also informs us of the type of loan contract, so there is information about whether the firm obtained credit for investment or for project financing in which case we also can deduce that firm is less likely to be credit constrained. There is also detailed evidence on maturity, interest rates, collaterals of loans and delinquency, among other relevant credit information.

Our financially restricted measures have most of the desired properties Silva and Carreira (2010) mention, such as being simple, objective, firm specific and time varying. Furthermore, given our financial restricted measures we may understand better investment cash flow sensitivity in Brazil.

We think that our paper contributes in an important way to empirical literature, because our measures of financial restrictions are original, and more accurate than the ones that exist in the literature so far and that we describe briefly above. The reason we think like this is that we construct them by analyzing credit information of firms directly from their loan contracts with financial institutions.

age. Farre-Mensa and Ljungqvist (2016) analyze accuracy of some measures of financial restrictions that we mention in the text.

[5] Cherchye et al. (2020) propose a new and interesting methodology for measuring financial constraints of firms related to their productivity and based on balance sheet and survey information.

[6] In the Literature Sector that follows this Introduction, we will discuss in more detail the downsides of these measures.

We can also apply our methodology to listed firms, or even individuals and for any period or data frequency as high as one day. In addition, our identification strategy does not depend on balance sheets, reports, or survey information of firms, which have several disadvantages.

Our results show that our financial restriction measures explain well access of firms to credit for investment as well as indicate that their investment is negatively related to financial restrictions in Brazil. Furthermore, our results also show the importance of the relationship between productivity and financial restrictions to understand investment demand of private firms in Brazil.[7]

The remainder of the paper is the following. Section 2 describes in more detail empirical literature on financial constraint measures and how they may impact investment and productivity of firms. Section 3 describes the data. Section 4 presents our empirical identification strategy. Section 5 shows the results of empirical exercises related to the impact of financial frictions on investment demand. Section 6 presents a simple partial equilibrium dynamic stochastic control model of investment with financial frictions. Section 7 concludes.

2. Literature Review of Financial Constraints Measures of Firms

2.1 Measures of Financial Restrictions and Investment

The theoretical literature examining the relationship between financial constraints and corporate investment is rooted in the relaxation of the perfect market hypothesis established by Modigliani and Miller (1958). Their theorem posits that, in frictionless capital markets, external and internal financing are perfect substitutes. Consequently, a firm's capital structure and financial policy should remain irrelevant to its investment decisions.

[7] Our paper is, in some ways, related to Jiménez et al. (2014). The authors explore in details loan´s information of Banco Spaña Credit Register. Different from Jiménez et al., however, our paper does not have the loan applications of firms. However, our identification strategy avoids this problem, because if a firm needs credit, Bester (1985) shows, that in a competitive market of financial institutions, there will be a menu of loan contracts available for this firm.

However, subsequent research by Stiglitz and Weiss (1981) and Myers and Majluf (1984) documented how capital market imperfections—stemming from agency problems—disrupt this neutrality. The presence of moral hazard and adverse selection creates a "wedge" between the costs of internal and external funds. These asymmetries may drive credit prices to supra-optimal levels or lead to credit rationing, preventing firms from achieving their optimal growth and investment targets.

These informational asymmetries are particularly acute for small and young firms, given their lack of established records and the resulting scarcity of publicly available information (Petersen and Rajan, 1994; 1995). In such contexts, lenders struggle to assess risk quality or monitor investment behavior, making these firms more susceptible to credit constraints.

Conversely, Bester (1985) suggests that credit rationing may not occur in equilibrium if banks use collateral requirements and interest rates as screening mechanisms to distinguish between high- and low-risk borrowers.

Empirical research on financial constraints follows three methodological strands: indirect measures, direct measures, and indices. Direct measures utilize surveys and qualitative reports, while indices synthesize various firm characteristics.

Indirect measures, the most prominent strand, focus on the sensitivity of investment to cash flow. The fundamental premise of indirect measurement is that high investment-cash flow sensitivity indicates a firm is financially constrained. To evaluate this, researchers typically segment firms' ex-ante into constrained and unconstrained groups based on balance sheet characteristics such as total assets, age, number of employees, or credit ratings. In these empirical models, Tobin's average Q is employed to control investment opportunities, while cash flow variables serve as proxies for financial slack.

Nonetheless, indirect measures face significant criticism regarding the use of average Q as a proxy for marginal q (Tobin, 1979). Neoclassical theory identifies marginal q as the theoretically correct measure for investment opportunities, yet it remains unobservable. Erickson and Whited (2000) argue that average Q is often a poor proxy, potentially leading to statistical imprecision. Furthermore, Cleary et al. (2007) suggest that cash flow itself may contain information about future profitability, confounding its role as a measure of liquidity constraints.

A further limitation is that Tobin's Q is only calculable for publicly listed firms, despite the fact that private firms—which often lack market valuations—are theoretically more bank-dependent and credit-constrained. To address this, Gala et al. (2020) propose an alternative framework for estimating investment demand without relying on market-based Q values.

The seminal empirical study in this field by Fazzari, Hubbard, and Petersen (1988) uses dividend policy to classify firms, arguing that low-dividend-paying firms are more likely to be constrained. Their findings showed that investment in these firms was significantly more sensitive to cash flow fluctuations. This conclusion was later challenged by Kaplan and Zingales (1997), who use qualitative data from annual reports to argue that Fazzari et al.'s classification was flawed and that constrained firms actually exhibited lower sensitivity. This critique was supported by Cleary (1999) and Dasgupta and Sengupta (2007), the latter finding a non-monotonic relationship between investment and cash flow shocks.

An alternative approach by Almeida et al. (2004) shifts the focus from investment to cash-to-cash-flow sensitivity. They argue that constrained firms must systematically save a portion of their cash flow to fund future projects, whereas unconstrained firms, enjoying ready access to external markets, do not need to manage cash stocks as rigorously. Therefore, the propensity to save money out of cash flow serves as a robust indicator of financial constraints.

Almeida et al. (2004) claim that the level of financial constraints can be measured by the sensitivity of cash stock to cash flow. The rationale behind is that, while constrained firms need to save cash out of cash flows to take advantage of future investment opportunities, unconstrained firms do not, as they are able to resort to external finance. Meanwhile, firms that hold cash incur opportunity costs associated with present investment opportunities. As a result, only constrained firms will need to optimize their cash stocks over time to maximize their profits and hedge future shocks by holding cash. Therefore, one can expect that estimates on the sensitivity of cash to cash-flow.

Another facet of the literature highlights that cash-flows might contain information about the firm's investment opportunities, meaning that Q should be corrected, as Alti (2003) and Bhagat et al. (2005) point out. Alti finds that even after Q correction, every firm in his sample shows sensitivity to cash-flow. In addition, Bhagat et al. find evidence that financially distressed firms exhibit positive investment-cash flow sensitivities if they operate at a profit, low sensitivity if operate at a loss.

Close bank relationships facilitate the contact between firms and banks, reducing information asymmetries, which means lower financing constraints for firms (if such relationships are stable). As Diamond (1991) argues, the risk associated with any loan is not neutral with respect to the duration of the relationship. As a result, one can expect differences in financial constraints between market-oriented economies, such as United States, and more bank-oriented economy, like Germany.

An interesting empirical paper that studies firm´s bank relationships is Karainov et al. (2010). The authors examine whether financial constraints affect firms' investment decisions by comparing a group of unbanked firms to firms that rely on bank financing. Specifically, they combine data from the Spanish Mercantile Registry and the Bank of Spain Credit Registry (CIR) to classify firms according to their number of banking relations: one, several, or none. They show that financial constraints are negatively related to the number of bank relationships firms have.

In the case of direct measures, one can read the annual reports of firms and look for words or expressions of word that give some hint of financial difficulties a firm is facing such as Kaplan and Zingales (2007) did. Otherwise, one can prepare surveys for firms to answer one or more questions related to their cost of external funds, credit denials, and availability of external funds, as in, for example, Campello et al. (2010), Beck et al. (2008), ECB´s survey on the access to finance of enterprises (SAFE) and Ferrando and Mulier (2013).

Regarding qualitative assessments, Kaplan and Zingales (1997) pioneered the use of content analysis in annual reports, identifying specific linguistic markers and expressions symptomatic of liquidity distress. Alternatively, direct measures may be constructed through firm-level surveys. In this framework, enterprises are directly queried regarding their perceived financial status. This categorization is typically achieved through either a single binary indicator or a multidimensional set of questions addressing the cost of external capital, instances of credit denial, and the general availability of external funding.

However, direct measures possess inherent methodological drawbacks similar to those of indirect indicators. The subjective nature of self-assessed variables introduces potential biases rooted in managerial perception. Furthermore, such data is often resource-intensive to collect, frequently scarce, and may lack the granularity required for robust econometric analysis. Ideally, survey data should be cross verified with information from financial institutions; however, such proprietary data is rarely accessible to researchers.

Several prominent studies have utilized this survey-based approach. Campello et al. (2010) conducted a large-scale survey of 1,050 Chief Financial Officers (CFOs) across 39 countries in North America, Europe, and Asia during the 2008 financial crisis. By contrasting the strategic actions of constrained versus unconstrained firms, the authors demonstrated that their survey-derived measure identifies significant cross-sectional variations in corporate behavior during periods of systemic economic stress.

Similarly, Beck et al. (2008) utilized survey data to examine whether financial development disproportionately alleviates growth obstacles for small firms compared to large enterprises. Their findings provide critical insights into the mechanisms through which financial deepening fosters aggregate economic expansion.

Finally, the European Central Bank’s Survey on Access to Finance of Enterprises (SAFE) serves as a comprehensive longitudinal instrument. It documents the evolving financial condition of firms and tracks trends in the demand for and supply of external financing. The SAFE dataset allows for granular analysis, as results are disaggregated by firm size, economic sector, jurisdiction, age, financial autonomy, and ownership structure. Conducted semi-annually, it remains a primary source for monitoring the transmission of financial constraints within the Eurozone.

The primary advantage of survey-based methodologies lies in the fact that firms are the most informed agents regarding the quality and viability of their own projects. Consequently, it is reasonable to assume that investment opportunities are implicitly internalized within managerial responses. Furthermore, surveys facilitate the assessment of financial constraints for small and young firms that do not publicly disclose balance sheets—a cohort typically excluded from studies relying on indirect measures. To enhance the robustness of survey data, qualitative responses can be integrated with quantitative firm-level information.

Islam and Meza (2023) contribute to the literature on direct measures by synthesizing data on external finance usage and credit application outcomes to construct a comprehensive metric of financial constraints. Their framework refines previous methodologies by incorporating granular data on partial versus full loan approvals, a distinction made possible by recent improvements in survey instruments. Utilizing a vast dataset of over 100,000 firms across 219 surveys in 144 economies, they find that approximately 30 percent of the formal private sector firms is credit constrained. Their evidence suggests that such constraints are more prevalent among smaller enterprises and that the share of constrained firms diminishes as the economy becomes more developed.

The third strand of the literature involves the construction of indices, which aggregate both direct and indirect measures. While these indices benefit from the inclusion of both qualitative and quantitative data, they also inherit the respective limitations of their constituent parts. Two of the most prominent metrics in the literature are the Kaplan-Zingales (1997) Index and the Whited-Wu (2006) Index.

The Kaplan-Zingales (KZ) Index provides a relative measure of a firm's reliance on external financing. A high KZ score indicates that a company is more likely to encounter difficulties when financial conditions tighten, potentially hindering the financing of ongoing operations. The index is derived from a five-factor model comprising cash flow, Tobin's Q, total debt, dividends, and cash holdings.

In contrast, the Whited-Wu (WW) Index is derived from a Generalized Method of Moments (GMM) estimation of an investment demand Euler equation. In this framework, the Lagrange multiplier associated with the external financing constraint represents the shadow cost of external capital. This shadow cost is modeled as a function of six factors: the ratio of cash flow to assets, a dividend payer dummy, the ratio of long-term debt to total assets, firm size, sales growth, and industry-level sales growth.

In a recent methodological contribution, Cherchye et al. (2020) propose a novel framework in which financial constraints are modeled as the foregone profitability resulting from binding budget constraints on production inputs. This approach posits that credit frictions impede firms from deploying optimal levels of inputs and technology, thereby forcing production below efficient scales. By integrating balance sheet data with survey-based, self-reported financial constraints, their measure captures latent frictions beyond observable firm characteristics. This methodology effectively recovers both cross-sectional and time-varying stylized facts of financial constraints and is applicable to both publicly traded and private enterprises.

Expanding on the multidimensional nature of credit frictions, Musso and Schiavo (2008) develop a time-varying, continuous index of financial restrictions. This synthetic index collapses information from multiple variables to capture varying degrees of constraint intensity. Analyzing French manufacturing firms between 1996 and 2004, the authors demonstrate a significant correlation between financial health and market longevity: as financial constraints intensify, the probability of firm survival diminishes, leading to an increased rate of market exit.

The real-sector implications of these constraints became particularly evident during recent systemic shocks. Khan (2022) investigates the impact of the COVID-19 pandemic, demonstrating that credit-rationed firms were significantly more susceptible to acute liquidity and cash flow distress. Compared to their unconstrained counterparts, these firms exhibit a higher propensity for delinquency in meeting obligations to financial institutions. Furthermore, credit-constrained firms faced restricted access to bank funding as a primary liquidity source, exacerbating the financial volatility induced by the pandemic-driven economic crisis.

2.2 Financial Restrictions and Productivity

As Heil (2017) shows, a growing body of empirical evidence identifies financial development as a critical determinant of productivity growth, while conversely, financial frictions result in significant productivity losses. Both idiosyncratic and cross-country studies converge on the conclusion that various financial frictions impede productivity by obstructing the optimal allocation of resources. These frictions may stifle competition, impair capital investment, hinder the adoption of advanced technologies, and distort incentives for efficient capital deployment. Furthermore, evidence suggests that financial frictions account for a substantial portion of the productivity gap observed between developed and developing economies.

Ferrando and Ruggieri (2015) examine the nexus between financial constraints and labor productivity using a unique firm-level dataset across several Eurozone countries from 1995 to 2011. Their findings indicate that firms in Italy and Portugal are most adversely affected by financial limitations, with an estimated labor productivity loss of approximately 21%.

In a theoretical and empirical contribution, Levine and Warusawitharana (2021) model the relationship between financial restrictions and productivity, positing that heightened constraints increase the sensitivity of productivity growth to external financing. Testing this prediction on a large sample of primarily private European firms, the authors find robust empirical support. Their results underscore a vital link between financial markets and the real economy, explaining why economic activity often remains persistently depressed following systemic financial crises.

Cao and Leung (2020) identify firm size, current leverage (debt-to-asset ratio), and cash flow as robust indicators of financial constraints, whereas the long-term debt-to-asset ratio appears statistically insignificant. In estimating firm-level Total Factor Productivity (TFP) while accounting for credit constraints, the authors find that omitting these constraints results in an upward bias in productivity estimates by approximately 4%. Additionally, while they find no definitive evidence that credit constraints directly slow the rate of productivity growth, they confirm that both investment and employment growth are negatively impacted by measured financial restrictions.

The impact of financing constraints is particularly pronounced for firms engaged in Research and Development (R&D), given the inherent risks and intangibility associated with such investments. As previously established, credit market inefficiencies create a wedge between internal and external financing costs, establishing a clear financing hierarchy. Hall (1992) and Himmelberg and Petersen (1994) provide empirical support for the hypothesis that R&D investment is significantly credit-constrained, particularly among small firms. These findings are further corroborated by Hall et al. (1999) in a comparative study of French, Japanese, and American firms, reinforcing the global relevance of financial barriers to innovation.

3. Data

We have two sources of data. The balance sheet and financial information of private firms (hereafter firms) come from Valorpro. [8] Valorpro has the advantage of having balance sheet information mostly on firms of medium and large sizes. The information of firm´s loan contracts come from SCR.

Our database has unbalanced balance sheets and financial information of 6,215 firms from 2012 to 2022. Table 1 shows that there are 6,089 joint stock and 126 limited liability firms. We classify these firms into 5 sectors, following the classification scheme of Valorpro: Agriculture, Commerce, Energy, Industry and Services. Most firms come from the services sector (2,409).

[Insert Table 1]

Table 2 Panel A displays the descriptive statistics (mean and standard deviation) of main balance sheet and financial information of firms in our sample.[9] The largest ones, measured by the natural logarithm of total sales (ln_sales) and total assets (ln_assets) come from the energy sector followed by the commerce sector. The highest average investment (capex_assets) occurs in the agricultural sector. The most profitable sector, measured by the average ratio between ebitda and total assets (ebitda_assets), is the agriculture sector and the one with the highest leverage (measured by ln_netlib) is the energy sector. In terms of annual growth of operational revenues (varoper), the energy sector has the highest average value. Table 2 Panel B shows correlation matrix of the main variables we use in our empirical exercises.

[8] Valorpro is a database of balance sheet and financial information of firms. It is a proprietary database of Brazilian economic journal *Valor Econômico.*
[9] Appedix 1 shows the definition of variables that we use in the paper.

[Insert Table 2]

In case of loan contracts, we use the information on SCR. The SCR is an outstanding database of almost all loan contracts written between individuals and firms with financial institutions in Brazil in a certain period. Our interest in this paper is to study loans of firms.

SCR has flow, stock, and cadastral information on these loan contracts. In case of cadastral information, for example, SCR informs the date the firm was opened, and how long firm has a relationship with a financial institution, among many other information. In case of flow information, one can observe, among other features of the loan contracts, interest rate charged, guarantees, maturity, type of loan contract, and credit risk of the loan. Stock information, for example, shows whether firm loans have more than 90 days delinquency, the relative importance of bad loans in relation to the total portfolio of loans, the number of bank relationships the firms have, among other information.

Figure 1 shows the total number of loan contracts written every year from 2012 to 2020 by firms in our sample registered at SCR. It is interesting to observe that there is a sharp decline in the number of contracts between 2020 and 2021. We conclude that this may have happened because of a decrease in GDP growth related to the Covid-19 pandemic.

[Insert Figure 1]

We classify the type or motive of the loan contract in three categories: working capital, financing and investment or project finance. Working capitals are all sorts of loans that are not for financing or investment reasons. Examples of these kinds of loans are bank discounts of credit instruments, secure overdraft facilities, credit card receivable financing, among many others.

Financing loans, on the other hand, exist for the purchase of goods, whether mobile or not. Normally, and as a rule, interest rates are lower and maturities are higher for financing loans than for those working capital loans, since the financed asset is, normally, given as collateral until the debt is paid off. Moreover, we have information about loans for project financing or investment, which is crucial for our empirical identification strategy, because it indicates firms that are acquiring these loans to increase their capital stock.

Figure 2 presents the percentage of types of loans contracts of the firms in our database from 2012 to 2022. Figure 2 shows that working capital loans exceed by far loans for financing and investment or project financing in all years.

[Insert Figure 2]

Table 3 Panels A and B, respectively, show mean and standard deviation of main information of loan contracts that we use in our paper. [10] It is important to observe that the mean of age does not increase every year. The reason for this is that not all of the firms in our sample wrote a loan contract with a financial institution in every year of our sample. We, also, only consider loans in which one year interest rate, tx1_y is positive. In the case of collaterals, when no information is available, we consider that the value of collateral is zero.

[Insert Table 3]

4. Empirical Identification Strategy

4.1 Identification of Financial Restriction Measures

In this paper, to measure financial restrictions, we will follow an identification strategy, related to Contract Theory, based on Bester(1985). Bester shows, using a very elegant mathematical model, that no credit rationing will occur in equilibrium if banks compete and choose collateral requirements and the rate of interest to screen investor´s riskiness. Therefore, it becomes possible to use different contracts as a self-selection mechanism, or in another words, to use them as a form of revelation mechanism. [11]

In the words of Bester (1985), credit rationing equilibrium will always pool good and bad risks. If this pooling occurs, then there exists another credit offer that is profitable because it attracts only the good borrowers. Therefore, an equilibrium will be characterized by separation of borrowers with low probability of default from borrowers with high probability

[10] Appendix 2 presents the definition of the variables.
[11] See Myerson (1979).

of default. The latter will choose contracts with a higher interest rate and lower collateral than borrowers with low probability of default.

Thus, interest rates and collaterals serve as screening mechanisms financial institutions use to separate good borrowers from bad ones.[12] As Stiglitz and Weiss (1981) indicate, adverse selection feature of interest rates is a consequence of different borrowers having different probabilities of repaying their loans. Bester (1985) points out that collateral may also serve to reveal information about the default risk of loan applicants and that in an equilibrium, the level of collateralization is negatively related to the riskiness of the borrowers´ investment projects. Collaterals may be explained as a response to imperfect information.

One could criticize our use of Bester (1985) model, since it assumes a competitive credit market, and in Brazil, as it is well documented, credit supply is concentrated in a few financial institutions. However, Taback et al. (2015) and Nakane (2002) show empirical evidence that credit supply in Brazil can be best characterized by monopolistic competition. Not only that, in recent years, BCB has implemented a serious of initiatives to create more competition in financial markets.[13]

Our identification strategy, following Bester (1985), analyzes 11,967,603loan contracts written between 6,215 private firms and financial institutions from 2012 to 2022 to sort out some of these firms that are considered more financially restricted, looking at relative levels of their interest rates and collateral contracted with financial institutions in this sample period. These loan contracts, as we mentioned above, come from SCR of BCB.

A possible relevant problem with the identification strategy mentioned above is that, for some reason, financial institutions may have, for a certain time, deviate from what would be their optimal credit policies, as we emphasize in the Introduction. This could have had an influence on our capacity to identify borrowers with different levels of riskiness. For example, Joaquim et al. (2023) explore a large intervention implemented by Brazil´s government in credit markets with the use of two large commercial government banks: Banco do Brasil (BB) and Caixa Economica Federal (CEF). The policy was characterized by an increase in credit at low

[12] See Myerson (1979).
[13] For example, we can list open finance and positive cadaster.

interest rates by the government banks, which, it was presumed, would lead to a reduction in interest rates by private banks, and to an increase in credit access. [14]

To avoid the possibility mentioned above, we adapt Bellucci et al. (2021) . The authors show that methods that do not allow for endogenous contract terms detect a positive reciprocal association between interest rate and collateral. On the contrary, methods that allow for endogenous contract terms point to a strong positive effect of interest rate on collateral but the effect of collateral on interest rate is weaker. This highlights the importance of incorporating the endogenous nature of contract terms in empirical work.

Therefore, to incorporate this endogenous nature of contract terms, we decide to use Three Stage Least Square Model (hereafter 3SLS) for every year[15] of our sample period with interest rate and collateral of firms as dependent variables and several characteristics of financial institutions, borrowers, and firms as well as types of loans as exogenous or instrument variables. The objective is to predict in sample interest rates and collaterals that would better reproduce optimal credit policies of financial institutions.

We present our 3SLS model for every year of our sample period in Equation (1) below. The dependent variables are per year interest rate of the loan (tx1_y) and natural logarithm of collateral of the loan (ln_collateral).

Matrix X is formed by exogenous variables. They are age of the firm measured in days, the natural logarithm of maturity of loans, and the risk of the loan, which an integer number from 1(low risk) to 4(high risk).

Matrix Z is formed by instruments for both equations. They are related to the credit characteristics of private firms, financial institutions, and types of loans. In the case of credit characteristics of firms, we use as instrument a binary variable equal to 1 if the firm has loans with delinquency over 90 days, and zero otherwise. In the case of credit characteristics of banks,

[14] Schmitz(2020) documents that federal banks manifest their social motivation by expanding their credit operations with smaller firms in Brazilian states with lower GDP at a relatively higher growth rate. Nevertheless, federal banks accomplish this by increasing their credit relationships with riskier firms.
[15] We decide to estimate as a pool for every year, instead of estimating a panel because our sample period is characterized by several macroeconomic shocks that could complicate our identification strategy.

we use a binary variable if financial institution is a government and 0 otherwise; we also create a dummy variable equal to 1 if financial institution are one of the five commercial banks that are responsible for around 85% of loans in Brazil and 0 otherwise.[16] In the case of types of loans, we define a dummy variable financing equal to one if the purpose of the loan is to finance a good or 0 otherwise; and finally, a dummy variable investment equal to 1 if the loan is for investment or 0 otherwise.

$$\begin{aligned} tx\_y_{it} &= \alpha_0 + \gamma \ln \_collateral_{it} + \beta X_{it} + u_{it} \\ \ln \_collateral_{it} &= \delta_0 + \rho tx\_y_{it} + \theta X_{it} + e_{it} \end{aligned} \quad (1)$$

Instruments for both equations: Matrix Z_{it}, i=1 to 6215 and t=2012 to 2022

After estimating the model, we forecast interest rate and collaterals within sample for every year of our sample period. We use the 30% percentile of the distribution of forecast of ln_collateral (Q30_ln_collateral) and the 70% percentile of forecast interest rate (Q70_tx1_y) as our benchmarks. Figure 3 and 4 present these quantities from 2012 to 2022.

[Insert Figure 3]

[Insert Figure 4]

We define a firm as more likely to be financially restricted in a certain year if the maximum value of its natural logarithm of collateral (ln_collateral) is lower than Q30_ln-collateral and maximum interest rate (tx1_y) is higher than Q70_tx1_y. We think that these definitions make it possible to sort firms that Bester(1985) shows financial institutions consider as those more likely to be bad borrowers or to be financially constrained.

Figure 5 shows the number of firms that we define as financially restricted throughout our sample period. The maximum number of financially restricted firms occurred in 2022 (1,215 firms) and the lowest happen in 2012, and the lowest in 2012 (101 firms).

[Insert Figure 5]

Figure 6 presents the number of financially restricted firms separated by the sectors of the economy. As one can easily observe, in every year of our sample period most financially

[16] The banks are: Banco do Brasil S/A Caixa Econômica Federal, Bradesco S/A, Itaú S/A, Santander S/A.

restricted firms come from the services sector and industrial sectors, while the number of firms from the agricultural sector that are financially restricted is the lowest.

[Insert Figure 6]

Figure 7 shows the percentage of financially restricted firms that are young or old for every year of our sample. We have the age of every firm in our sample period. In a certain year, we consider firm young (old) if its age is lower (higher) than the 30% percentile (70% percentile) of distribution of age of all firms that wrote loan contracts with financial institutions in that year. As one can observe, in all years of our sample, there are more young than old firms. However, it is important to note that not all the firms that we define as financially restricted are young. Thus, any ex-ante classification of financially restricted firms based on age solely, is probably creating a sample bias.

[Insert Figure 7]

Figure 8 presents the percentage of financially restricted firms that are large or small. The financial institutions that record loan to firms in SCR inform what they consider to be the size of the firm. This variable varies from 1(small) to 5 (large). Therefore, we have the size of every firm for every loan contract that we observe. As one can observe, in all years of our sample, there are no large firms financially restricted. However, an important warning must be made, once again, because not all of our financially restricted firms are small. So once more, an ex-ante classification of financially restricted firms based only on size would lead to sample bias.

[Insert Figure 8]

Figure 9 shows the percentage of financially restricted firms that have short-term and long-term relationship with financial institutions in our sample. In SCR, we have information on the date firms and financial institutions started their relationship. Given that we also know the date of every loan contract, we can find, for every contract, for how long firm and financial institution have been transacting. In a certain year, we consider firm to have a long relationship (short relationship) if this variable, measured in days, higher (lower) than the 70% percentile

(30% percentile) of distribution of time of relationship of all firms that wrote loan contracts with financial institutions in that year. As one can observe, in all years of our sample, short-term relationship is more common than long-term ones for financially restricted firms.

[Insert Figure 9]

Figure 10 presents the percentage of investment loans of financially restricted firms for every year. It is striking to observe that in most years there are no loans of this kind. The highest percentage of these loans occur in 2020. However, they are less than 1% of the total loans made by these firms. This, in our view, is important evidence that these firms either are using internal resources to invest or are not investing at all, because they do not have due to credit restrictions.

[Insert Figure 10]

In Figures 11, we look at how financial institutions compare the risks of loans of financially restricted and non-financially restricted firms. In the loan contracts registered at SCR, financial institutions inform what they consider to be the level of riskiness of the loans they make. It is a number from 1 (low risk) to 4 (high risk). We take the average of this variable for every year and for loans of these two groups of firms. As one can observe, financial institutions consider loans of financially restricted firms much more risk that those of non-financially restricted ones. make some comparisons between loans written by financially and non-financially restricted firms.

[Insert Figure 11]

Figure 12 shows the average number of loans of financially restricted and non-financially restricted firms for every year. It is outstanding to observe that, in all years, former firms have much less loans on average than in latter firms. This, in our view, is *prima facie* evidence that these firms have much less access to credit than other non-financially restricted firms

[Insert Figure 12]

Table 5 Panel A presents mean tests of some characteristic of financially and non-financially restricted firms that we take from SCR. As one can perceive in all years of our sample, there is statistical evidence that financially restricted firms have contracts with higher interest rate, lower collateral, higher risk, are smaller, and have short-term relationship with financial institutions than non-financially restricted firms. Table 5 Panel show mean tests of balance sheet characteristics of financially restricted and non-financially restricted firms. In this case, there is statistical evidence that financially restricted firms are smaller, either measured by sales or assets, than non-financially restricted firms.

[Insert Table 5]

In sum, we think Figures 5 to 12 as well as Table 5 indicate that our identification strategy of financially restricted firms sorts out firms that are mostly young, small, use internal resources to invest or do not have investment opportunities, come mostly from the services or industrial sectors, and write fewer loans with financial institutions than non-financially restricted firms.

In next section, we will use our financial restriction measure in two different sets of exercises. One is empirical one and the other is a simulation of a continuous time stochastic model of investment.

5. Exercises with our measures of financial restrictions of private firms in Brazil

5.1 Introduction

We perform two different sets of exercises associated with financial restriction measures that we create above. In the first one, we estimate several demand models of investment of firms without using any measure of Q of Tobin following Gala et al. (2020). In the second one, we simulate a dynamic stochastic partial equilibrium model of investment in continuous time, considering as our main hypothesis that financial restrictions negatively affect total factor productivity of firms.

5.2 Investment Demand

5.2.1 Main Empirical Analyzes

In our main empirical analysis, we estimate Equation (2) below, using panel data, firm fixed effects and time fixed effects, adapting Gala et al. (2020). Gala et al. estimate investment policy functions under general assumptions about technology and markets. They present a dynamic structural model of corporate investment behavior, without assumption about homogeneity and perfect competition. The authors exploit the fact that the optimal investment policy can always be directly estimated as a function of key state variables of the firm. They show that their policy functions are easy to estimate and, in addition, summarize the key predictions of any dynamic investment model. Because their method does not rely on Tobin's Q, it does not require information about market values and can be applied to analyze private firms, which are the objects of our study in this paper.

The dependent variable is Equation (2) is the ratio between capex and assets. We create a dummy variable, FR, which is equal to one if the firm is financially restricted and zero otherwise.[17] As a measure of cash flow, we use the first difference of operational revenue (varoper) and as a measure of size we use the natural logarithm of total sales (ln_sales). We also include a variable that measures net liabilities, which is the difference between total liabilities and cash (ln_netlib). We estimate with fixed firm´s effects (a_i) and time fixed effects (v_t), correcting for heteroscedasticity with robust matrix with sectors of the firms as cluster variable.[18]

The null hypotheses that we want to evaluate is that the coefficient (β_1) of FR is negative. We estimate two specifications, one with the regressor ln_netlib and the other without it.

$$\frac{capex_{it}}{assets_{it}} = \beta_0 + \beta_1 FR + \beta_2 varoper_{it} + \beta_3 \ln\_sales_{it} + \beta_4\, \mathrm{fr}_{it} \ln\_netlib_{it} + a_i + v_t + u_{it} \quad (2)$$

[17] See the Identification Strategy Sector of the paper.

[18] Appendix A1 presents the definitions of all variables we use in our regressions.

Table 6 displays the results and show that investment is negatively related to financial restrictions. The coefficients of FR are negative in both estimations and statistically significant. Our results are also economically significant, as restricted firms decrease their capex in relation to their assets from a minimum of 3.66% to a maximum of 4.57%. relative to non-financially restricted firms

[Insert Table 6]

5.2.2 Robustness Exercises of Estimations of Investment Demand

5.2.2.1 Different Specifications of Investment Demand

We estimate several regressions like Equation (2) above and centered on Gala et al. (2020), substituting some regressors by other ones or including new ones in main specification.

In Table 7, Panels A to C, we show the results of these robust exercises. In Panel A, we include other regressors in our main specification, such as natural logarithm of total assets (ln_assets), ratio between fixed assets and total assets (fixed_assets) as additional measures of size and ratio between cash and total assets(cash_assets) as a measure of liquidity. In Panel B, we include macroeconomic variables in our main specification, for instance year average of Selic interest rate (selic) and GDP growth (gdp). In Panel C, we substitute natural logarithm of sales (ln_sales) by natural logarithm of assets (ln(assets) as a measure of size of firm. The results displayed in Table 7 Panels A to C confirm those we obtain in our main empirical analyses, that is, investment of firms is negatively related to financial restrictions.

[Insert Table 7]

5.2.2.2 Endogeneity

In a second attempt to verify the robustness of our main empirical results, we contemplate possible endogeneity of all regressors of Equation (2), except for dummy of financial restrictions, FR. The instrumental variables are one and two lags of these regressors. We perform Hausman (1978) tests of model specification, comparing fixed effects estimations with instrumental variables estimations. The null Hypotheses of the test is that coefficients of fixed effects estimation and instrumental variable estimation are consistent. In this case, if the null Hypothesis is not rejected, there is statistical evidence of no endogeneity.

Table 8 shows the chi-square statistics and p-values. They show that for regressions with and without variable natural logarithm of net liabilities (ln_netlib), that the null of the Hausman test is not rejected, in which case there is statistical evidence that fixed effects estimations give better estimates than instrumental variables estimations. Thus, results shown in Table 8 confirm our main empirical results shown above.

5.2.2.2 Treatment Effects Estimations

We implement Treatment Effects Estimations, such as Nearest Neighbor Matching (hereafter NN), Propensity Score Matching (hereafter PSM) and Difference-in-Difference (hereafter Dif-in-Dif). We report in Table 9 Average Treatment Effects (ATE) and Average Treatment Effects of the Treated Statistic (ATET) statistics of the difference of the ratio between capex and assets (capex_assets) for NN and PSM estimations and ATET for Dif-in-Dif estimations.

In the case of NN, the treatment variable is a dummy variable that indicates a firm is financially restricted (FR), matching variable is a measure of size, natural logarithm of total sales (ln_sales), and the regression is identical to Equation (1). In the case of PSM, the matching is based on a regression of a dummy that indicates financial restriction, with respect to the size, also measured by natural logarithm of total sales (ln_sales), and the regression is the same as Equation (1). Finally, in the case of dif-in-dif regressions, the treatment variable is a dummy indicating the existence of financial restrictions and the regression is the same as the one in Equation (1).

Table 9 Panel A show the results for NN estimations. In this case, ATE and ATET have a negative sign but are not statistically significant. Table 9 Panel B displays the results for PSM. It shows that ATEs have negative signs, but also not statistically significant, while ATET have positive signs but also not statistically significant. Finally, for Dif-in-Dif estimations, ATET, in the regression without natural logarithm of net liabilities (ln_netlib), is negative and statistically significant, while ATET for the regression with ln_netlib is negative but not statistically significant.

5.2.2.3 Measurement Errors of Financial Restrictions of Firms

Another reasonable and relevant concern of our main results presented in Table 6 is related to our identification of financially (or not) restricted firms. Our criteria can be questioned in several ways. It can be wrong, or it may not describe all the possibilities in which firms could be subject to financial constraints.

To oversee possible measurement error in the dummy variable FR, which measures financial restrictions, we follow Griliches and Hausman (1986). The authors suggest, before using instruments to correct measurement errors in panel data with fixed effects, to perform a specification test, such as Hausman (1978) test of fixed effects against random effects estimations. The latter estimated using Generalized Least Squares (GLS), while the former use Ordinary Least Squares (OLS). The intuition for this is that a measurement error, if it exists, would be part of the total error of the panel regression. Therefore, if Hausman test does not reject the Null Hypothesis that coefficients of both fixed and random effects estimations are consistent, than there is evidence of no measurement error and one would choose the fixed effects estimation.

Table 10 Panels A and B present the chi-square statistic and p-value associated with Hausman (1978) test for fixed effects against random effects, with and without time fixed effects. The results show no statistical difference between coefficients of fixed and random effects regressions, that is, no rejection of Null Hypothesis of the test.

Despite having no statistical evidence, using Hausman (1978) test, of measurement errors we decide to estimate a model of instrumental variables for FR variable.[19] We use as instruments the first lag of FR and pandemic, which is a dummy variable equal to one in the pandemic period (2020) and zero otherwise. We display the results in Table 10 Pane C and they indicate, once again, that financial restriction negatively affect investment of firms.

[19] The statistics of Hausman (1978) test are valid asymptotically. We have a small sample. Therefore, in this case, there is a possibility that Hausman (1978) test may be inaccurate.

5.3 Partial Equilibrium Dynamic Stochastic Modell of Investment

In this section, we simulate a simple Partial Equilibrium Dynamic Stochastic Model of Investment. The model is an extension of the neoclassical model of Tobin (1969). There is a representative firm that chooses optimally investment in a continuous time stochastic dynamic framework. The objective function is the present value of cash flow of the firm, which depends on the costs of adjustment of investment. There is a productivity shock that is stochastic and affects production function.

Following Ferrando and Ruggieri (2015), Levine and Warusawitharana (2021), and Cao and Leung (2020), we expect that financial restrictions will have a negative impact on productivity of firms, which, as a consequence, will have negative effect on their optimal levels investments.

The problem representative firm solves is the following:

$$Max_{X_t}\, E \int_0^{\infty} e^{-\bar{r}t}\left(Z_t K_t^{\alpha} - X_t - \theta\left(\frac{X_t}{K_t}\right)^2 K_t^2\right) d_t$$

s.t.

$$\dot{K}_t = X_t - \delta K_t$$

$$dZ_t = \mu(Z_t)dt + \sigma(Z_t)dW_t$$

K_t^{α} is production function; K_t is capital stock; X_t is investment; Z_t is productivity; $\theta\left(\frac{X_t}{K_t}\right)^2 K_t^2$ is the cost of adjustment of investment defined as a quadratic function of the ratio between investment and capital stock; parameter δ is depreciation rate, $\bar{r}$ is the discount rate and W_t is a Brownian motion.

We model productivity of firms as a convex combination of productivity of financially restricted firms and non-financially restricted firms. The productivity model is as an Ornstein-Uhlenbeck diffusion process: for financially restricted firms the process is: $dlogZ_t =$

$-\theta_1 logZ_t dt + \sigma_1{}^2 dW_{1t}$. The process for non-financially restricted firms is: $dlogZ_t = -\theta_2 logZ_t dt + \sigma_2{}^2 dW_{2t}$. Therefore, the productivity of representative firm will have the following diffusion process dynamics: $dlogZ_t = p(-\theta_1 logZ_t) + (1-p)(-\theta_2 logZ_t)dt + p\sigma_1{}^2 dW_{1t} + (1-p)\sigma_2{}^2 dW_{2t}$ and $\rho = corr(dW_{1t}, dW_{2t})$. We can think of p ε [0,1] as the probability of the firm being financially restricted.

We calibrate our model in the resulting manner: θ_1=average growth rate of productivity of the services sector from 2012 to 2022.; $\sigma_1{}^2$ is the variance of the growth rate of productivity of the services sector from 2012 to 2022;θ_2=average growth rate of productivity of the agricultural sector from 2012 to 2022; $\sigma_2{}^2$ is the variance of the growth rate of productivity of the agricultural sector from 2012 to 2022 ; $\bar{r}$ is the discount rate and it is equal to 5% p.y.; $\theta = 0.5$. [20,21]

We simulate the model for several values of p, from 0.0 to 1.0 , and for values of ρ from -1 to 1. The simulations give us optimal investment policies, which are the ratios of investment to capital stock as functions of capital stock for a certain p and ρ.

We assume the case where the optimal investment policy for all ρ is related to p=0 (firm has no financial restrictions) as our benchmark. We create two other series for all ρ . The first one is the ratio between optimal investment policies with p equal to 0.10 and optimal investment policy with p=0. The second one is the ratio between optimal investment policies with p equal to 0.10 and optimal investment policy with p=0.[22]

Figures 13 to 15 present the dynamics of these series respectively for ρ equal 0, 1 and -1 respectively. As one can easily observe, as firms become more likely to be financially restricted their optimal investment ratios tend to decrease as capital stock increases, compared to non-financially restricted firms.

[20] For the productivity process of financially restricted firms, we use data coming from the service sector, which I, together with industrial sector, the one with more firms in this situation. For the case of productivity of non-financially restricted firms, we take on data from the agricultural sector, which is the one with fewer firms as financially restricted. We obtain these quantities at https://ibre.fgv.br/observatorio-produtividade.

[21] We adapt the matlab program firm.m that can be found at https://benjaminmoll.com/codes/ for our simulations. The code of the program we use is in Appendix 3 of the paper.

[22] We use 0.10 because it is close to the mean plus one standard deviation the series of percentage of financially restricted firms in every year.

6. Conclusion

Our main objective in this paper is to create financial restriction measures based on microdata related to financial institutions loan contracts written with of Brazilian private firms and study how or if they affect investment demand of these firms. We look at 11,967,603loan contracts written between 6,215 private firms and financial institutions in this period.

Our financial restrictions measures do a good job in explaining the credit market of some small and medium size firms in Brazil and indicate that their investment policies are negatively related to the degree of their financial restrictions.

We ponder that our paper contributes in relevant ways to empirical literature and in terms of policy. Considering the former, our paper creates original measures of financial restrictions that, we think, are more accurate than the ones that exist in literature so far. As far as we know, our paper is the first one in the literature to construct these measures by analyzing information directly from loan contracts of firms with financial institutions. In terms of latter, we ponder that our financial restriction measures can be used by policy makers to have a better understanding of the stance of the credit market for private firms in Brazil.

We can also apply our methodology to listed or private firms and for any period or data frequency as high as one day. Furthermore, our methodology does not depend on balance sheets, reports or survey information of firms.

Future research could expand the number of firms to be studied and use higher frequencies than a year. It could also use firm´s loans contract in SCR to try to infer agency costs, due to information asymmetries and moral hazards, which, we conjecture, could improve the financial restriction measures that we build in this paper.

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Table 1 Firms and Sectors

Our database has unbalanced balance sheets and financial information of 6,215 firms from 2012 to 2022. The database come from Valorpro. We classify these firms into 5 sectors, following the classification of Valorpro: Agriculture, Commerce, Energy, Industry and Services.

Sectors	Joint Stock	Limited Liability	Total
Agriculture	204	0	204
Commerce	765	8	773
Energy	920	5	925
Industry	1,863	41	1,904
Services	2,337	72	2,409
Total	6,089	126	6,215

Table 2 Descriptive Statistics

Our database has unbalanced balance sheets and financial information of 6,215 firms from 2012 to 2022. We classify these firms into 5 sectors, following the classification of Valorpro: Agriculture, Commerce, Energy, Industry and Services. Panel A shows mean and standard deviation (second number below) of balance sheet characteristics separated by sectors of the economy. Panel B shows correlation of these balance sheet characteristics.

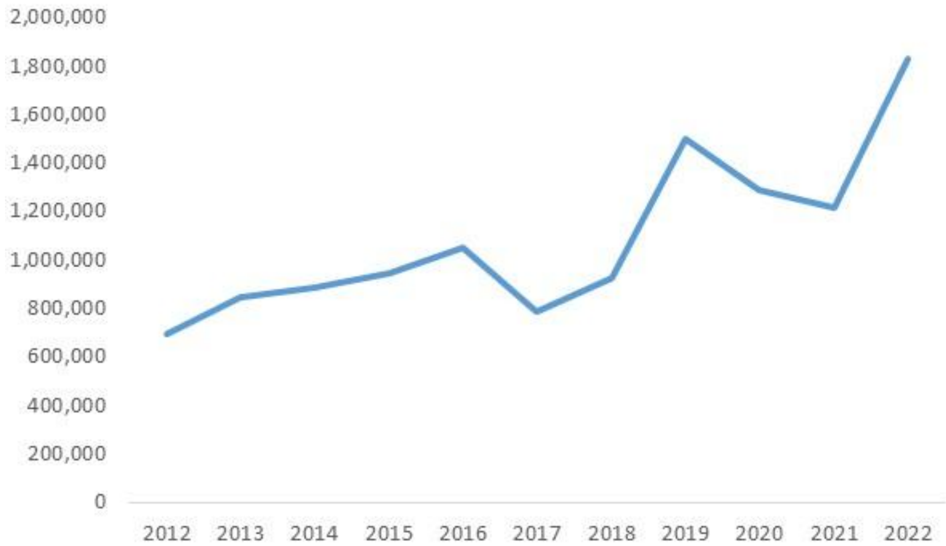
Panel A Mean and Standard Deviation Private Firms

	Agriculture	Commerce	Energy	Industry	Services
capex_assets	3.6511	0.1213	0.1468	0.0515	0.3037
	18.6803	1.3809	0.6013	0.1725	8.3218
ln_sales	5.5134	5.7072	6.1992	5.6635	5.2053
	1.9485	1.8197	2.0576	1.7405	1.6990
ln_assets	3.2752	5.1488	6.5377	5.4503	5.4250
	2.0949	1.7747	1.8788	1.7152	1.9005
ln_netlib	4.2406	4.8656	6.1180	4.8772	5.1119
	2.3232	2.7222	2.8544	2.7308	2.8833
varoper	0.0357	-0.0304	0.0109	0.0270	0.0300
	0.6372	0.5963	0.6374	0.6394	0.6486
fixex_assets	22.2852	0.1931	0.5295	0.4657	0.3811
	57.8569	0.2095	0.4693	0.3655	0.4802
ebitda_assets	32.7146	0.0863	0.1280	0.0759	0.7572
	45.9641	0.2744	0.8003	0.3256	0.0756
cash_assets	6.4070	0.2474	0.2084	0.4625	0.3235
	27.7001	5.6065	2.6763	10.0715	9.4993

Panel B Correlation Matrix

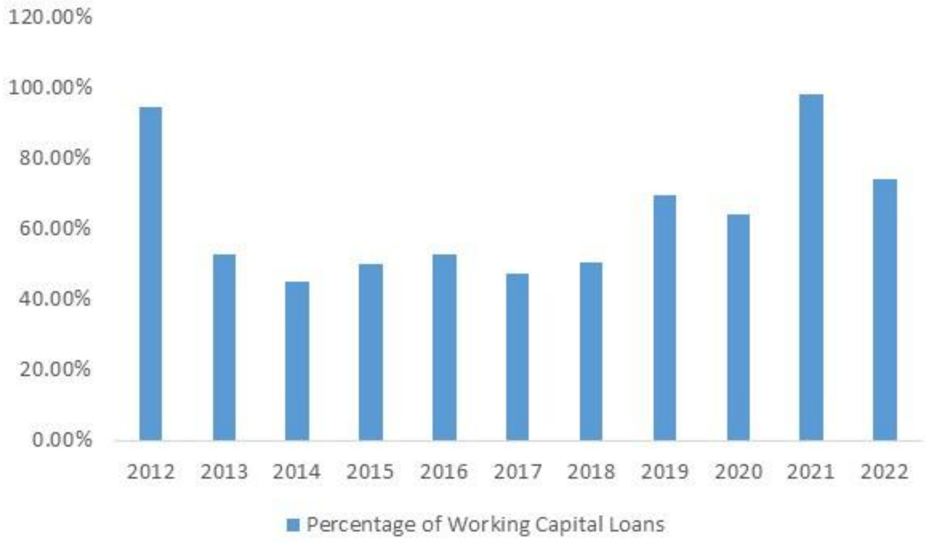
	capex_assets	ln_sales	ln_assets	ln_netlib	varoper	fixed_assets	ebitda_assets	cash_assets
capex_assets	1	-0.036137	-0.09002	-0.052561	0.001739	0.043939	-0.002607	0.186337
ln_sales	-0.036137	1.000000	0.526103	0.341930	0.140001	0.046283	-0.006472	-0.09293
ln_assets	-0.090020	0.526103	1.000000	0.668600	0.160588	-0.068993	-0.05401	-0.135616
ln_netlib	-0.052561	0.341930	0.668600	1.000000	0.078886	-0.065401	-0.06472	-0.074949
varoper	0.001739	0.140001	0.160588	0.078886	1.000000	0.026819	-0.001734	-0.024771
fixed_assets	0.043939	0.046283	-0.068993	-0.065401	0.026819	1.000000	0.020974	0.012682
ebitda_assets	-0.002607	-0.006472	-0.054010	-0.064720	-0.001734	0.020974	1	-0.027065
cash_assets	0.186337	-0.092930	-0.135616	-0.074949	-0.024771	0.012682	-0.027065	1

Figure 1 Number of Loan Contracts of Private Firms in Brazil from 2012 to 2022



Source: System of Credit Register (SCR) of BCB
Note: These are registered loans of 6,215 private firms written with financial institutions in Brazil from 2012 to 2022.

Figure 2 Percentages of Working Capital Loans



Source: System of Credit Register (SCR) of BCB
Note: Working Capital Loans are types of loans that are not financing or investment.

Table 3 Descriptive Statistics of Data from Loan Contracts

Table 3 Panels A and B, respectively, show mean and standard deviation of main information of loan contracts that we use in our paper. See Appendix for a description of variables in this Table. We consider loans in which one year interest rate, tx1_y is positive. In the case of collaterals, when no information is available, we consider that the value of collateral is zero. Source of data is SCR.

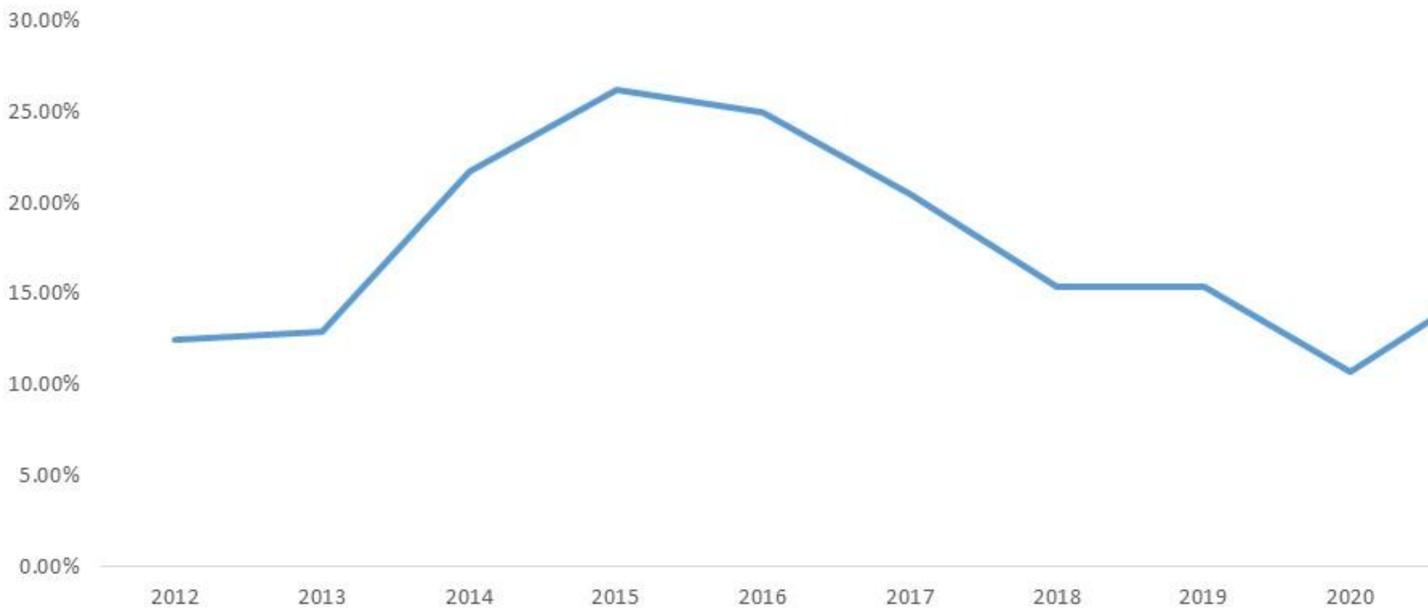
Panel A Mean Values

	2012	2013	2014	2015	2016	2017
tx1_y	10.39853	12.82873	15.07962	19.8558	20.63801	14.19718
ln_guarantee	0.789654	0.406287	0.261488	0.406287	0.463492	0.153278
ln_maturity	1.422455	4.371185	1.429154	1.41411	1.393002	1.38575
age	11134.63	10397.84	13407.42	11595.53	6691.265	13147.57
relationship	4945.694	4555.754	4179.573	4243.891	4429.207	8375.405
ln_value_loan	2.092034	8.001663	2.065776	7.648113	7.782733	6.485246
risk	0.00582	0.008091	0.003865	0.004077	0.002453	0.008549
size	3.576836	3.555117	3.691351	3.712826	3.80381	3.714171

Panel B Standard Deviation Values

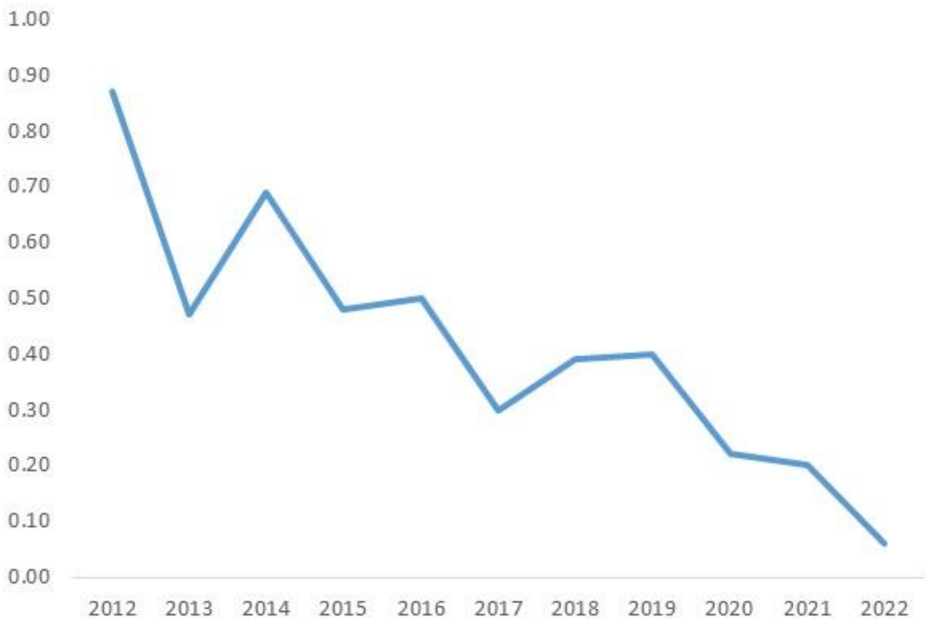
	2012	2013	2014	2015	2016	2017
tx1_y	4.5228	5.4733	5.8960	6.7811	6.6887	6.7854
ln_guarantee	2.7949	2.2365	1.7783	2.2365	2.3850	1.3557
ln_maturity	0.328259	1.212741	0.267341	0.243159	0.243997	0.325053
age	6006.968	5994.931	5073.7	6011.157	4464.631	5640.101
relantionship	3577.246	3196.696	4082.038	4773.102	3069.337	5155.287
ln_value_loan	0.350552	2.868378	0.330077	3.339243	3.095084	3.054137
risk	0.350552	2.868378	0.330077	3.339243	3.095084	3.054137
size	0.822849	0.85835	0.70236	0.655698	0.547776	0.621274

Figure 3 Percentile 70% of predicted tx1_y



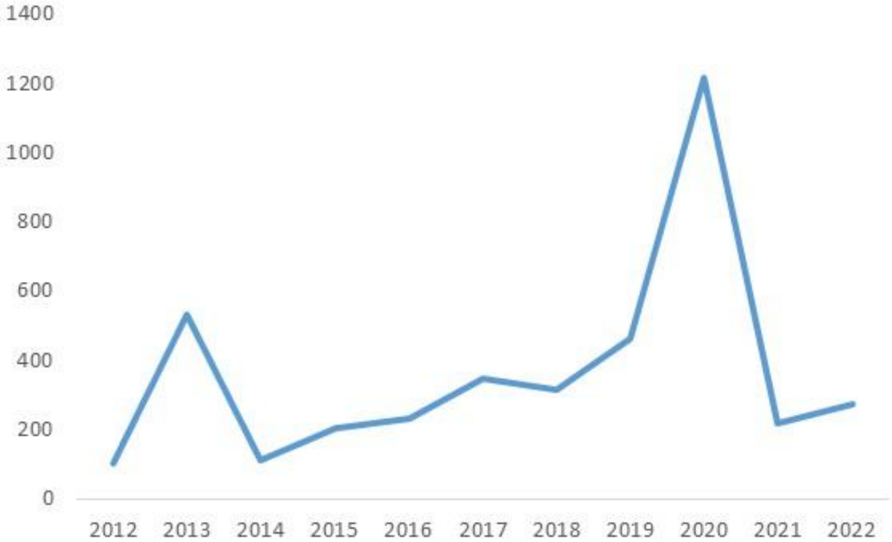
Source: System of Credit Register (SCR) of BCB
Note: After estimating the 3SLQ model, Equation (1) in the text, we forecast in-sample interest rate (tx1_y) for every year of our sample period. We use the 70% percentile of forecast tx1_y as benchmark(Q70_tx1_y)

Figure 4 Percentile 30% of predicted ln_guarantee



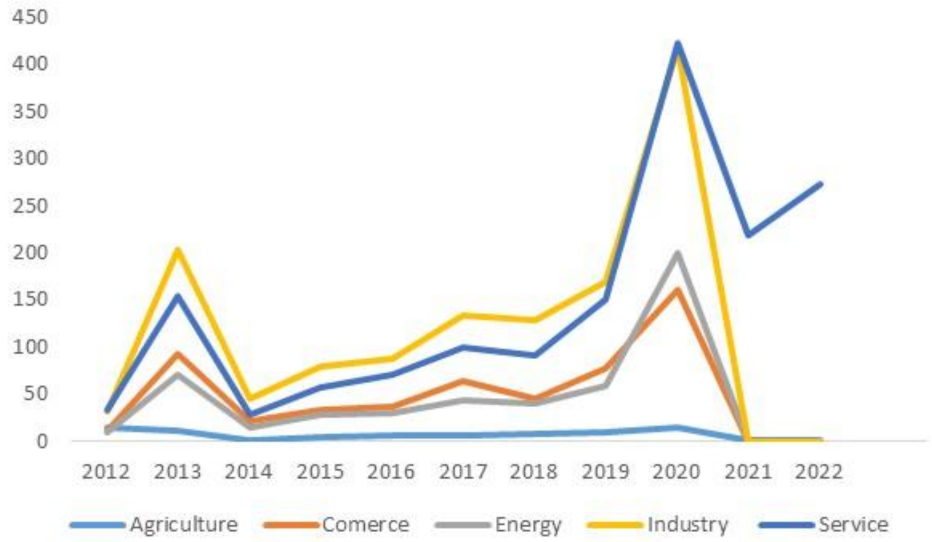
Source: System of Credit Register (SCR) of BCB
Note: After estimating the 3SLQ model, Equation (1) in the text, we forecast in-sample natural logarithm of collateral (ln_collateral) for every year of our sample period. We use the 30% percentile of forecast of ln_collateral as benchmark(Q30_ln_collateral)

Figure 5 Number of Firms Financially Restricted



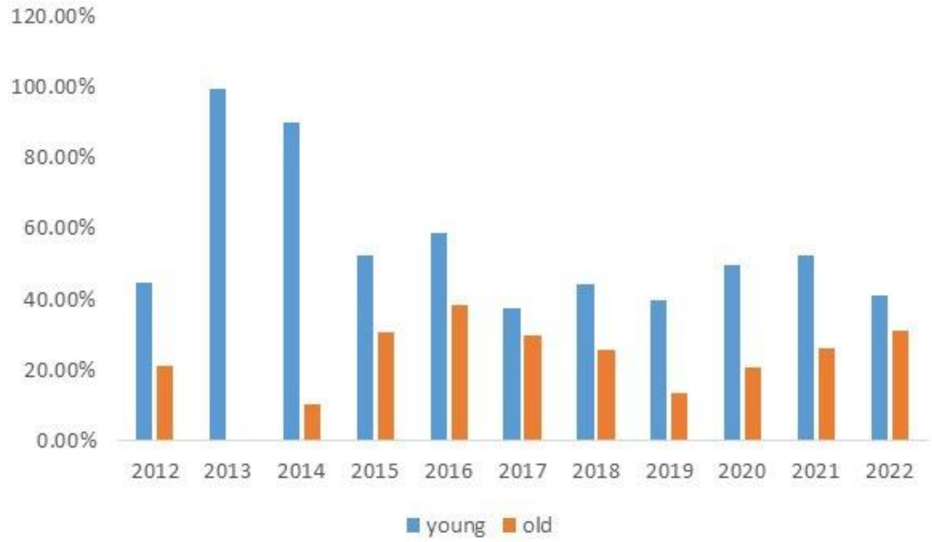
Source: System of Credit Register (SCR) BCB
Note: We define a firm as more likely to be financially restricted in a certain year if the maximum value of its natural logarithm of collateral (ln_collateral) is lower than Q30_ln-collateral and maximum interest rate (tx1_y) is higher than Q70_tx1_y.

Figure 6 Number of Financially Restricted Firms and Sectors



Source: System of Credit Register (SCR) BCB
Note: We define a firm as more likely to be financially restricted in a certain year if the maximum value of its natural logarithm of collateral (ln_collateral) is lower than Q30_ln-collateral and maximum interest rate (tx1_y) is higher than Q70_tx1_y. The classification in Sectors comes from Valorpro.

Figure 7 Age of Financially restricted firms

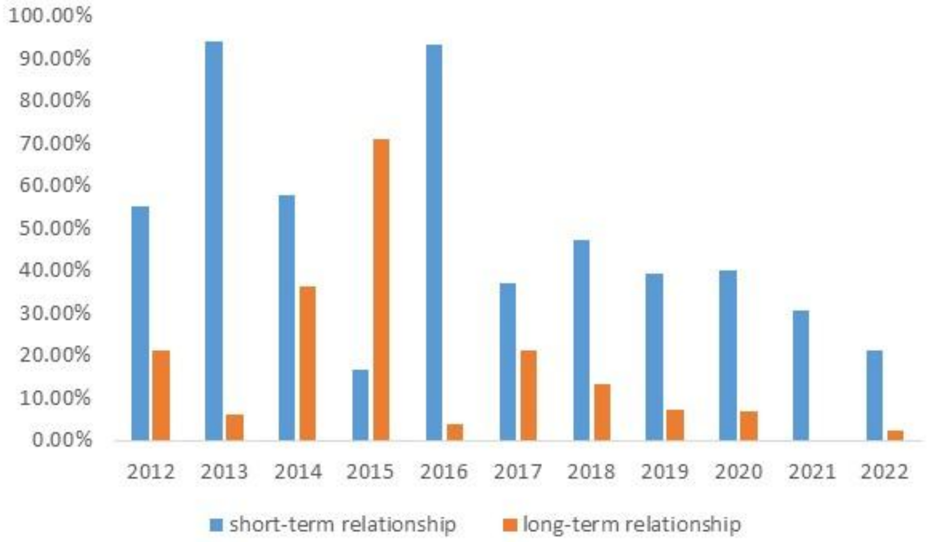


Source: System of Credit Register (SCR) BCB
Note: We have the age of every firm in our sample period. In a certain year, we consider firm young (old) if its age is lower (higher) than the 30% percentile (70% percentile) of distribution of age of all firms that wrote loan contracts with financial institutions in that year.

Figure 8 Size of Financially Restricted Firms

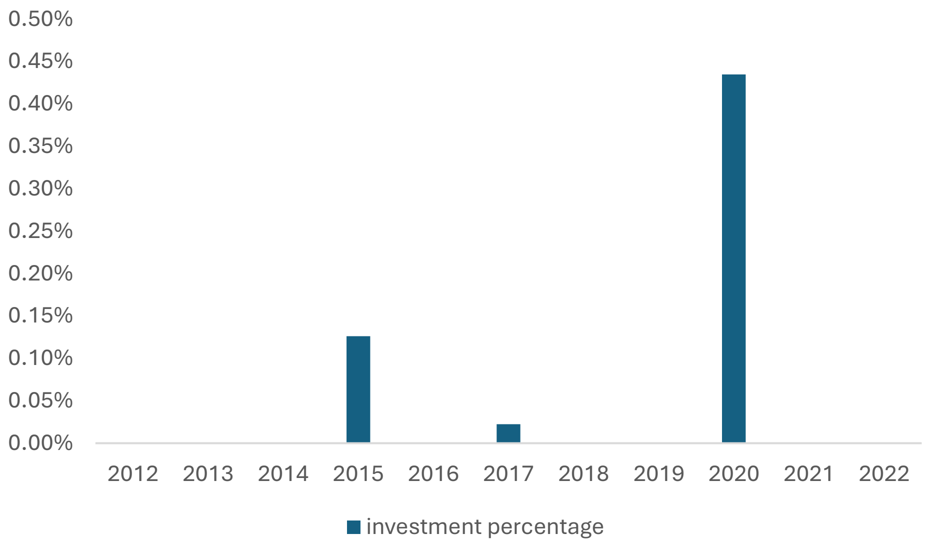
Source: System of Credit Register (SCR) BCB
Note: The financial institutions that record loans to firms in SCR inform what they consider to be the size of the firm. This variable varies from 1(small) to 5 (large).

Figure 9 Time of Relationship with Banks of Financially Restricted Firms



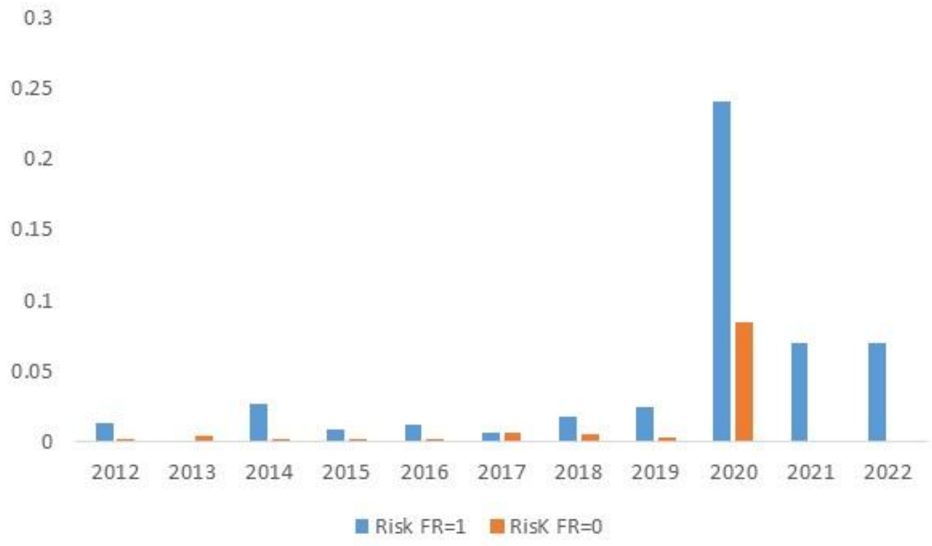
Source: System of Credit Register (SCR) BCB
Note: We have information on the date firms and financial institutions started their relationship. Given that we also know the date of every loan contract, we can find, for every contract, for how long firm and financial institution have been transacting. In a certain year, we consider firm to have a long relationship (short relationship) if this variable, measured in days, higher (lower) than the 70% percentile (30% percentile) of distribution of time of relationship of all firms that wrote loan contracts with financial institutions in that year.

Figure 10 Percentage of Investment Loans of Financially Restricted Firms



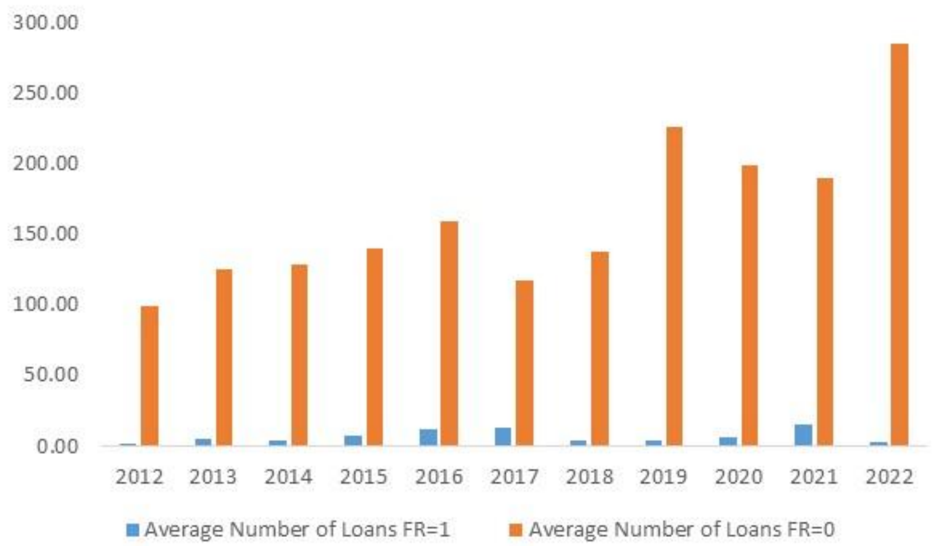
Source: System of Credit Register (SCR) BCB
Note: There is in SCR information on the types of loan, such as those for investment.

Figure 11 Comparison of Riskiness of Loans of Financially Restricted and non-Financially Restricted Firms



Source: System of Credit Registry SCR BCB
Note: In the loan contracts registered at SCR, financial institutions inform what they consider to be the level of riskiness of the loans they make. It is a number from 1 (low risk) to 4 (high risk). We take the average of this variable for every year and for loans of these two groups of firms.

Figure 12 Comparison of Average Number of Loan's of Financially Restricted and Non-Financially Restricted Firms



Source: System of Credit Registry SCR BCB

Table 5 Mean Tests of Difference in Loan Characteristics of Financially Restricted and Non-Financially Restricted Firms

Table 5 Panel A presents mean tests of some characteristic of financially and non-financially restricted firms that we take from SCR. In red, we show the statistic that is not significant. Table 5 Panel show mean tests of balance sheet characteristics of financially restricted and non-financially restricted firms. FR is equal to one if firm financially restricted and zero otherwise.

Panel A Loan Contracts

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
tx1_y	269.2906	251.5647	260.5605	192.5128	179.842	199.1388	214.5115	265.9595	254.3397	275.6961	276.4301
ln_guarantee	-43.10918	-27.00972	-32.07861	-26.9878	-30.00054	-21.63592	-28.128	-20.02474	-22.98797	-17.6045	-17.6045
risk	40.04796	38.66318	40.50058	40.29363	41.30399	38.25153	36.9404	40.12751	-0.716173	42.36907	42.34881
ln_value_operation	32.69026	-4.598414	1.074607	-2.893539	-2.850614	-2.689024	9.34876	33.47863	33.48282	33.35956	32.6902
ln_maturity	66.95047	-23.72833	57.26178	68.67835	68.82057	67.59546	67.34836	67.3403	67.70936	67.69035	67.05815
size	-107.4739	-91.6573	-136.4501	-144.2839	-189.714	-150.9651	-127.1951	-80.45156	-164.5024	-199.0771	-199.3304
age	0.081002	35.94815	-25.07922	26.79117	200.0398	25.74385	-9.508368	44.02575	-56.76607	-210.8388	-210.7267
relationship time	-11.26292	-26.11677	-18.90186	-21.3018	-33.38766	-33.30509	-73.17861	-77.03767	-124.7626	-121.0567	-122.4475

Panel B Mean Tests of Difference in Balance Sheet Characteristics between Financially Restricted and Non-Financially Restricted Firms
Note:

	FR=1 -FR=0
capex_assets	-0.21
ln_sales	-1.92**
varoper	-0.12
ln_netlib	-0.79
ln_assets	-2.66***
cash_assets	-0.93
ebitda_assets	0.10
fixed_assets	1.07

*p<0.10 ** p<0.05 ***p<0.01

Table 6 Main Investment Demand Estimations: Based on Gala et al. (2020)

We estimate Equation (2) in the text, using panel data, with firm and time fixed effects. Equation (2) is adapted from Gala et al. (2020). Gala et al. estimate investment policy functions under general assumptions about technology and markets and do not use average Q of Tobin. t statistics are under parentheses. The variable FR is one if the firm is financially restricted and zero otherwise.t statistics under parentheses.

	capex_assets	
	Eq. (1)	Eq. (2)
FR	-0.0457*	-0.3666***
	(-2.0976)	(-4.9241)
varoper	2.27E-06	-3.97E-03
	(1.8838)	(-0.2228)
ln_sales	-0.0125	0.3557*
	(-0.9578)	(2.3394)
netlib_assets	-0.0011	
	(-0.4955)	
_cons	0.1553	-2.6096**
	(2.2622)	(-2.8701)
fixed effects	yes	yes
time effects	yes	yes
sample period	2012-2022	2012-2022
Cluster Robust (sectors)	yes	yes
R2 within	0.053	0.01
F statistic all regressors	94.03***	70.21***
Number of Groups	887	2026
Number of Observations	1284	4346

p<0.10 ** p<0.05 ***p<0.01

Table 7 Robustness Exercises of Investment Demand Estimations

We adapt Gala et al. (2020) and estimate several regressions modifying the specifications of like Equation (2) above In Panel A, we include in our main specifications several balance sheet variables of private firms. In Panel B, we include macroeconomic variables, such as SELIC rate and GDP growth, in our main estimation. In Panel C, we substitute ln_sales for a new measure of size, which is ln_assets. t statistics are under parentheses. T statistics under parentheses.

Panel A Including Other Balance Sheet Variables

	capex_assets	
	Eq. (1)	Eq. (2)
FR	-0.0759***	-0.4074***
	(-4.1805)	(-3.7981)
varoper	1.157E-06***	-8.646E-07
	(2.9461)	(-0.4976)
ln_sales	-0.05433	0.4014**
	-0.9569	2.5702
netlib_assets	-0.0020	
	(-1.4768)	
cash_assets	0.5993	0.3997***
	(1.4977)	(3.3973)
fixed_assets	0.4411***	-0.2895***
	(20.5428)	(-4.9577)
ln_assets	0.0067	1.1752736***
	(0.1442)	(-2.6937)
cons	0.0067	1.1752736***
	(0.1442)	-2.6937
fixed effects	yes	yes
time effects	yes	yes
sample period	2012-2022	2012-2022
Cluster Robust (sectors)	yes	yes
F statistic all regressors		
R2 within	0.72	0.01
Number of Groups	870	1943
Number of Observations	1266	4255

*p<0.10 ** p<0.05 ***p<0.01

Panel B Including Macroeconomic Variables

	capex_assets	
	Eq. (1)	Eq. (2)
FR	-0.0457**	-0.3666***
	(-2.0976)	(-4.9241)
varoper	2.27E-06*	-3.965E-07
	(1.8838)	(-0.2228)
ln_sales	-0.0125	0.3557
	(-0.9578)	(2.3394)
netlib_assets	-0.0011	
	(-0.5000)	
_cons	0.4814*	-1.9271**
	(1.8149)	(-2.335)
Macroeconomic Controls	Selic, GDG growth	Selic, GDP growth
fixed effects	yes	yes
time effects	yes	yes
sample period	2012-2022	2012-2022
Cluster Robust (sectors)	yes	yes
R2 within	0.22	0.007
F statistic all regressors	1279.56	47.32
Number of Groups	844	1924
Number of Observations	1242	4160

*p<0.10 ** p<0.05 ***p<0.01

Panel C Size measured by natural logarithm of total assets (ln_assets)

	capex_assets	
	Eq. (1)	Eq. (2)
FR	-3.0100**	-1.046***
	(-2.7800)	(-10.68)
varoper	2.27E-04***	-1.65E-05
	(-2.672)	(-0.90)
ln_assets	-11.54***	-9.39
	(-3.26)	-(1.38)
netlib_assets	-0.3019	
	(-2.32)	
_cons	67.22***	51.2854
	(3.20)	(1.40)
fixed effects	yes	yes
time effects	yes	yes
sample period	2012-2022	2012-2022
Cluster Robust (sectors)	yes	yes
R2 within	0.28	0.025
F statistic all regressors	26.01	48.38
Number of Groups	1634	3393
Number of Observations	2601	4838

*p<0.10 ** p<0.05 ***p<0.01

Table 8 Hausman Test of Endogeneity

We contemplate possible endogeneity of all regressors of Equation (2), except for dummy of financial restrictions, FR. The instrumental variables are one and two lags of these regressors. We perform Hausman (1978) tests of model specification, comparing fixed effects estimations with instrumental variables estimations. The null Hypotheses of the test is that coefficients of fixed effects estimation and instrumental variable estimation are consistent. P-values are under parentheses.

Instruments	Eq(1)	Eq(2)
First Lags of:varoper,ln_sales, ln_netlib	0.1192	0.5598
	(0.9894)	(0.9055)
First and Second Lags of:varoper,ln_sales, ln_netlib	1.9415	0.5426
	(0.5846)	(0.9094)

Table 9 Treatment Effects Estimations

We implement Treatment Effects Estimations, such as Nearest Neighbor Matching (hereafter NN), Propensity Score Matching (hereafter PSM) and Difference-in-Difference (hereafter Dif-in-Dif). We report in Table 9 Average Treatment Effects (ATE) and Average Treatment Effects of the Treated Statistic (ATET) statistics of the difference of the ratio between capex and assets (capex_assets) for NN and PSM estimations and ATET for Dif-in-Dif estimations.

Panel A Nearest Neighbor (NN)

	Nearest-Neighbor	
ATE FR (1 vs 0)	-0.049	-0.041
(z statistic)	(-0.46)	(-0.20)
OBS	1284	4346
Matches (ln_sales)	2	2
ATET FR (1 vs 0)	-0.232	-0.18
(z statistic)	(-0.47)	(-0.6)
OBS	1284	4346
Matches (ln_sales)	2	2

Panel B Propensity Score Matching (PSM)

	Propensity Score Matching	
ATE FR (1 vs 0)	-0.095	-0.105
(z statistic)	(-1.12)	(-1.22)
OBS	7526	7526
Matches Logit regression (ln_sales)	2	
Matches Logit regression (ln_sales, ln_assets)		2
ATET FR (1 vs 0)	0.060	0.106
(z statistic)	(0.69)	(1.30)
OBS	7526	7526
Matches Logit regression (ln_sales)	2	
Matches Logit regression (ln_sales, ln_assets)		2

Panel C Difference in Diffeerence

	Dif-in Dif	
ATET FR (1 vs 0)	-0.045	-0.36**
(z statistic)	(-1.15)	(-3.59)
OBS	1284	4346
With ln_netlib	yes	no

Table 9 Considering Errors of Measures of Financial Restrictions

We follow Griliches and Hausman (1986) in Panels A and B. The authors suggest, before using instruments to correct measurement errors in panel data with fixed effects, to perform a specification test, such as Hausman (1978) test of fixed effects against random effects estimations. If Hausman test does not reject the Null Hypothesis that coefficients of both fixed and random effects estimations are consistent than this evidence of no measurement error and one would choose the fixed effects estimation. Chi square statistics and p-valuer are shown in Panels A and B. In Panel C, we estimate a model of instrumental variables for FR variable.[23] We use as instruments the first lag of FR and pandemic, which is a dummy variable equal to one in the pandemic period (2020) and zero otherwise. In Panel C, t statistics are under parentheses.

Panel A Hausman (1978) Test of Comparison between Fixed and Randon Effects with Time Fixed Effects

	EQ(1)	EQ(2)
Chi2	17.17	5.89
p-value	(-0.14)	(-0.88)
ln_netlib	yes	no
Time Fixed Effects	yes	yes

Panel A Hausman (1978) Test of Comparison between Fixed and Randon Effects with no Time Fixed Effects

	EQ(1)	EQ(2)
Chi2	0.79	0.33
p-value	(0.85)	(0.84)
ln_netlib	yes	no
Time Fixed Effects	no	no

[23] The statistics of Hausman (1978) test are valid asymptotically. We have a small sample. Therefore, in this case, there is a possibility that Hausman (1978) test may be inaccurate.

Panel C Panel Data with Endogenous Covariates and Fixed Effect

	capex_assets	
	Eq. (1)	Eq. (2)
FR	-2.5669*	0.38
	(-1.62)	(0.30)
varoper	1.66E-06	1.73E-06
	(0.31)	(2.09)
ln_sales	-0.057	-0.049
	(-1.11)	(-1.27)
ln_netlib	-0.0121	
	(-0.74)	
_cons	0.7100	0.70
	(2.14)	(1.97)
Instruments:FR(-1),pandemic	yes	yes
fixed effects	yes	yes
time effects	no	no
sample period	2012-2022	2012-2022
Cluster Robust (sectors)	yes	yes
R2 within	0.0003	0.0001
F statistic all regressors	3.52	19.94
Number of Groups	887	2026
Number of Observations	1284	4346

*p<0.10 ** p<0.05 ***p<0.01

Figure 13 Investment/Capital : ρ=0

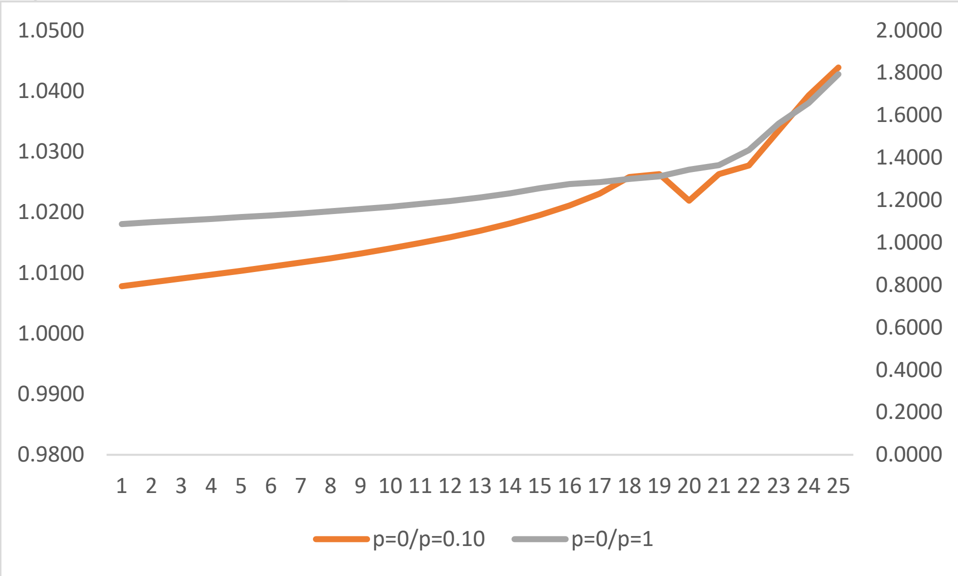


Figure 14 Investment/Capital : ρ=1

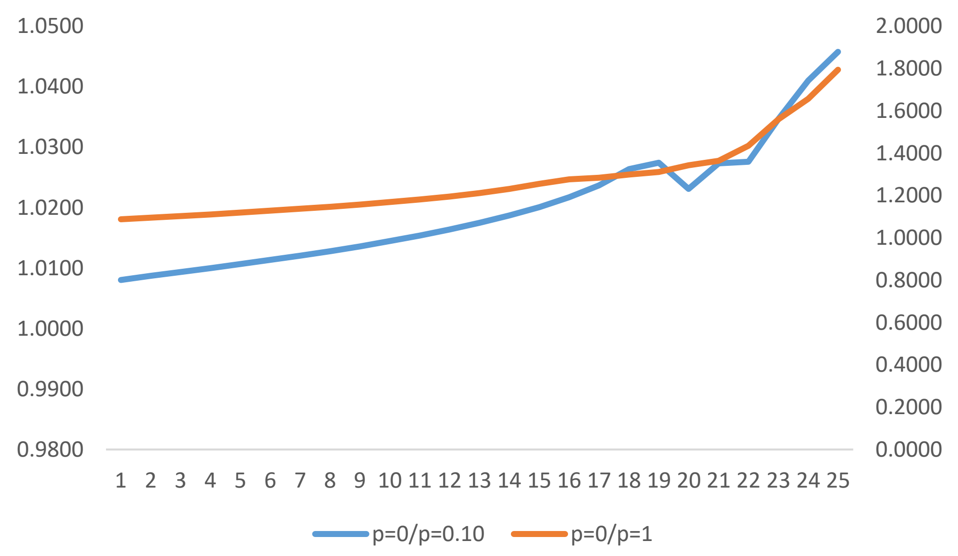
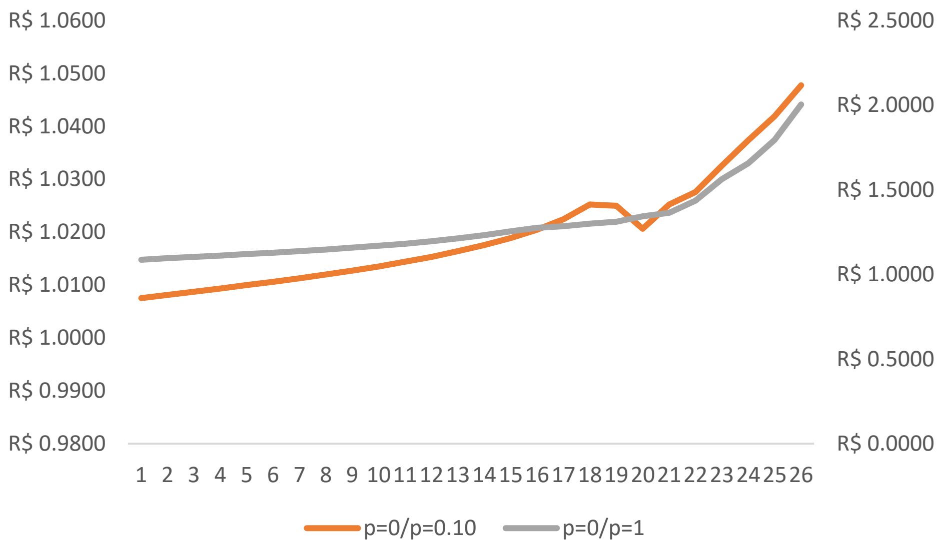


Figure 15 Investment/Capital : ρ=-1



Appendix A1 Variables Notations and Definitions

Variable	Definition
capex_assets	Ratio between capex and assets
varoper	first difference of operational revenue
ln_sales	natural logarithm of sales
netlib_assets	Ratio between net liabilities (total liabilities minus cash) and assets
varebitda	first difference of ebitda
fixed_assets	Ratio between fixed assets and assets
cash_assets	Ratio between cash and assets
ln_assets	natural logarithm of assets
selic	year average of selic rate
gdp	year growth rate of gdp
pandemic	equal to 1 in 2020 and 0 otherwise
ln_netlib	natural logarithm of net liabilities
FR	equal to 1 if firm financially restricted (see identfication strategy of paper) 0 otherwise
FR_OBS	equal to 1 if firm financially restricted using actual data) and 0 otherwise
FR_20_80	equal to 1 if firm financially restricted(identification similar to FR except for the use of percentiles 20 and 80) and 0 otherwise
FR_10_90	equal to 1 if firm financially restricted(identification similar to FR except for the use of percentiles 10 and 90) and 0 otherwise

Appendix A2 Definition of SCR Variables

Variable	Definition
tx1_y	one year nominal interest of the contract
ln_collateral	natural logarithm of collateral of contract
ln_maturity	natural logarithm of maturity of contract
ln_value_contract	natural logarithm of the value of the contract
age	diference between the date of contract and the date of opening of the firm
dif_rel	diference between the date of the contract and date the firm started transacting with the firm
size	size of the inform informed in the contract by the firm: a number of one to 5
Risk	risk of the contract informed by the firm: a number from 1 to 4

Appendix A3 Matlab Program for Simulation of Partial Equilibrium Dynamic Stochastic Control Model

```
clear all; close all; clc;
tic;

r = 0.05; %discount rate


%We adapt matlab rogram firm.m of XYZ.
%ORNSTEIN-UHLENBECK PROCESS dlog(z) = -the*log(z)dt + sig2*dW
%STATIONARY DISTRIBUTION IS log(z) ~ N(0,Var) where Var = sig2/(2*the)
%dz=(-zlog(z)the+1/2(zsig^2))dt+zsig*dw
%diffusion process of firms in our model:
%E[dw1dw2]=ro
%dlog(z)=-pthe1log(z)+psig1*dw1+(1-p)*the2log(z2)dt+(1-p)*sig2*dw2
% p is the probability of firm being financially restricted
%E[dw1dw2]=ro
col=0;
x_new=zeros(100,10);
for p=0.1:0.1:1.0
   col=col+1;
the=p*(-0.003)+(1-p)*(0.069);
ro=-1;
Var=(p^2)*(0.0674^2)+((1-p)^2)*(0.0449^2)+p*(1-p)*(0.0449*0.0674)*ro;
zmean=exp(the);
sig2=sqrt(Var);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%
J=40;
zmin = zmean*0.6;
zmax = zmean*1.4;
z = linspace(zmin,zmax,J);
dz = (zmax-zmin)/(J-1);
dz2 = dz^2;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
I=100;
kmin = 1;
kmax = 100;
k = linspace(kmin,kmax,I)';
dk = (kmax-kmin)/(I-1);

kk = k*ones(1,J);
zz = ones(I,1)*z;

mu = (-the*log(z) + sig2/2).*z;
```

```
s2 = sig2*(z.^2);
maxit= 20;
crit = 10^(-6);
Delta = 1000;
%%%%%%%%%%set
parameters%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%
alpha= 0.5;    %curvature in production function
theta=2.7;%%%% quadratic adjustment cost
delta=0.05; %%%depreciation rate
F = zz.*kk.^alpha;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
Vkf = zeros(I,J);
Vkb = zeros(I,J);
Vzf = zeros(I,J);
Vzb = zeros(I,J);
Vzz = zeros(I,J);
c = zeros(I,J);  %%c represents investment in equation 3

%CONSTRUCT MATRIX Bswitch SUMMARIZING EVOLUTION OF z
chi =  - min(mu,0)/dz + s2/(2*dz2);
yy =  min(mu,0)/dz - max(mu,0)/dz - s2/dz2;
zeta = max(mu,0)/dz + s2/(2*dz2);

%This will be the upperdiagonal of the B_switch

updiag=zeros(I,1); %This is necessary because of the peculiar way spdiags is defined.
for j=1:J
   updiag=[updiag;repmat(zeta(j),I,1)];
end

%This will be the center diagonal of the B_switch
centdiag=repmat(chi(1)+yy(1),I,1);
for j=2:J-1
   centdiag=[centdiag;repmat(yy(j),I,1)];
end
centdiag=[centdiag;repmat(yy(J)+zeta(J),I,1)];

%This will be the lower diagonal of the B_switch
lowdiag=repmat(chi(2),I,1);
for j=3:J
   lowdiag=[lowdiag;repmat(chi(j),I,1)];
end

%Add up the upper, center, and lower diagonal into a sparse matrix
Bswitch=spdiags(centdiag,0,I*J,I*J)+spdiags(lowdiag,-I,I*J,I*J)+spdiags(updiag,I,I*J,I*J);
```

```
%INITIAL GUESS
v0 =(F - delta*kk - 0.5*theta*delta^2*kk)/r;    %%%% attention please, need carefully check.
the U value at  steady state
v = v0;

%plot(k,v)

for n=1:maxit
    V = v;
    % forward difference
    Vkf(1:I-1,:) = (V(2:I,:)-V(1:I-1,:))/dk;
    Vkf(I,:) =   (1+theta*delta)*ones(1,J); %state constraint boundary condition
    % backward difference
    Vkb(2:I,:) = (V(2:I,:)-V(1:I-1,:))/dk;
    Vkb(1,:) =   (1+theta*delta)*ones(1,J); %state constraint boundary condition

    %investment with forward difference
    xf = (Vkf-1)/theta.*kk;
    sf = xf-delta.*kk;
    Hf = F - xf - 0.5*theta*(xf./kk).^2.*kk + Vkf.*sf;

    %investment with backward difference
    xb = (Vkb-1)/theta.*kk;
    sb =  xb-delta.*kk;
    Hb = F - xb - 0.5*theta*(xb./kk).^2.*kk + Vkb.*sb;

    %investment at steady state
    x0 =delta*kk;

    Ineither = (1-(sf>0)) .* (1-(sb<0));
    Iunique = (sb<0).*(1-(sf>0)) + (1-(sb<0)).*(sf>0);
    Iboth = (sb<0).*(sf>0);
    Ib = Iunique.*(sb<0) + Iboth.*(Hb>=Hf);
    If = Iunique.*(sf>0) + Iboth.*(Hf>=Hb);
    I0 = Ineither;

    x = xf.*If + xb.*Ib + x0.*I0;
    profits = F - x - 0.5*theta*(x./kk).^2.*kk;

    %CONSTRUCT MATRIX A
    X = - sb.*Ib/dk;
    Y = - sf.*If/dk + sb.*Ib/dk;
    Z = sf.*If/dk;

    %%%%spdiags   when updiag,0 first;when lowdiag,0 last.
    updiag=0; %This is needed because of the peculiarity of spdiags.
    for j=1:J
        updiag=[updiag;Z(1:I-1,j);0];
    end
```

```
    centdiag=reshape(Y,I*J,1);

    lowdiag=X(2:I,1);
    for j=2:J
        lowdiag=[lowdiag;0;X(2:I,j)];
    end

    AA=spdiags(centdiag,0,I*J,I*J)+spdiags([updiag;0],1,I*J,I*J)+spdiags([lowdiag;0],-
1,I*J,I*J);

    A = AA + Bswitch;

    if max(abs(sum(A,2)))>10^(-12)
        disp('Improper Transition Matrix')
        break
    end

    B = (1/Delta + r)*speye(I*J) - A;

    profits_stacked = reshape(profits,I*J,1);
    V_stacked = reshape(V,I*J,1);

    b = profits_stacked + V_stacked/Delta;

    V_stacked = B\b; %SOLVE SYSTEM OF EQUATIONS

    V = reshape(V_stacked,I,J);

    Vchange = V - v;
    v = V;

    dist(n) = max(max(abs(Vchange)));
    if dist(n)<crit
        disp('Value Function Converged, Iteration = ')
        disp(n)
        break
    end
end
toc;

%plot(k,v);

%plot(dist);:kdot = x - delta.*kk;;
%plot(k,kdot,k,zeros(I,1));
%plot(x(:,3))
    for j=1:100
       x_new(j,col)=mean(x(j,:));
    end
```

```
%plot(k,x_new(:,10))
%writematrix(x_new,"d:\inv3.xlsx")
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Solve linear system
AT=A';
b=zeros(I*J,1);
b(1,1)=0.1;
gg = AT\b;
g_sum = gg'*ones(40*I,1)*dz;
gg = gg/g_sum;

%g = [gg(1:I),gg(I+1:2*I)];

%check1 = g(:,1)'*ones(I,1)*dz;
%check2 = g(:,2)'*ones(I,1)*dz;
g=reshape(gg,I,J);
gk=zeros(I,1);
teste1=ones(40,1);
gk=g*teste1;
gk_teste=gk;
teste2=ones(100,1);
gk_sum=gk'*teste2;
gk=gk/gk_sum;
%gk_new=zeros(100,10);
%plot(k,gk);
 for t=1:1:100
       gk_new(t,col)=gk(t);
 end
 gk_k_new=[k,gk_new];
writematrix(gk_k_new,"d:\kf10.xlsx");
end
%teste3=gk_new(:,7);
%plot(k,gk);
gk_k_new
```