Measuring Financial Restrictions of Brazilian Private Firms with Microdata

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Abstract

Our contributions in this paper are twofold. In the first place, we build original financial restriction measures of 8,071 private firms in Brazil. We use these measures to have an idea of their level of financial restrictions from 2012 to 2020. To build these measures, we use microdata of 3,469,135 loan contracts written between these firms and financial institutions in this period. In the second place, we estimate, using our financial restriction measures, investment demand of these firms and verify if credit policies of the Banco Central do Brasil during the Covid-19 pandemic had any positive effect in mitigating their credit restrictions. Our results show that our financial restriction measures explain well the access of Brazilian private firms to credit for investment as well as indicate that their investment is negatively related to financial restrictions in Brazil. Furthermore, they also show that credit policies of Banco Central do Brasil had positive effect on working capital loans of private firms but did not have any effect on their investment in the Covid-19 pandemic period.

Keywords: financial restrictions measures, investment, private firms, Covid-19 pandemic, 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 carry out their optimal investment policies and growth trajectories. They are very important both in academia and for policy makers. In the case of the former, they are very relevant both in theoretical and empirical work related to Macroeconomics, Corporate Finance, Monetary Economics, Game Theory and Economics of Contracts. In the case of 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 constrains on firms' performance is very extensive. However, empirical contributions are rather 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 banks 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 banks 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, we will use a definition of financial restrictions related to the capacity a firm has to obtain credit with banks to implement positive present value investments or projects.[2] So, just to exemplify and make our definition clearer, let us suppose a certain firm has a positive present value investment and does not have all the monetary resources necessary to undertake this investment. The firm asks for loans in several banks for this purpose and all banks deny it. In accordance with our definition, this firm is financially constrained.

[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] This definition is a very common one in the empirical literature that measures financial restrictions (see Fazari, Hubard and Petersen (1988) for a discussion).

Of course, an empirical researcher wanting to verify if the firm is financially restricted or not would have enormous difficulty to do so, looking only at the loan data of this firm. To have a better grasp of this, she should have to ask the firm if it has a positive present value investment that it wants to implement and needs credit from banks for this and ask each bank that denied the credit for this purpose why it did so. This makes financial restrictions in empirical work non observable and hence very difficult to measure. No wonder, empirical researchers have been struggling for a very long time and devoting a lot of hard work in trying to measure financial restrictions of firms in appropriate manners.

Our main objective in this paper is to create financial restriction measures based on microdata related to bank loan contracts of Brazilian private firms. To understand how our measures of financial restrictions contribute to the empirical literature, it is important to describe very briefly the current state of the art of the 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.

Indirect measures look at the sensitivity of investment in relation to cash-flow. The fundamental idea is that if sensitivity is high, then there is an indication that the firm may be financially restricted. To test for this possibility, firms are separated in two groups- more likely to be financially restricted and less likely to be financially restricted- based on ex-ante classification related to balance sheet characteristics of firms.

The seminal empirical paper of indirect measures is Fazari, Hubbard and Petersen (1998). The authors use firm´s dividend policy to classify them in financially restricted or not. Firms that pay more dividends would be less likely, while firms that pay fewer dividends would be more likely to be financially constrained. The intuition behind this classification is that firms that pay fewer dividends use more internal resources to invest, since they have credit restrictions.[3]

[3] Kaplan and Zingales (1997) question this classification and show that many firms in the sample they used paid very little dividend but had no indication of being financially constrained. The authors cite Hewlett-Packard as an example of a firm of this sort.

There are many other ex-ante classification possibilities of financial restrictions based on balance sheet information of firms. One that is widely used and has the advantage of being exogenous is size (see Oliveira (2019) for Brazil´s data and Campelo et al. (2013)).[4]

Instead of looking at investment cash-flow sensitivities, Almeida et al. (2014) look at the cash policy of firms and analyze the cash sensitivity to cash-flow. The main idea of Almeida et al. is if a firm hoards cash, then it is probably because it wants to have enough liquidity to undertake its investments without asking banks for credit.[5]

Indirect measures have some drawbacks. The main concern is that all of them are associated with average Q of Tobin. This firm multiple is used to identify investment opportunities. Average Q of Tobin is a proxy for marginal q of Tobin (1969), which the neoclassical theory of investment considers to be the correct measure to identify the set of investment opportunities. The problem is that average Q may be a bad proxy for marginal q, as Erickson and Whited (2000) show. It may also be the case, as Clearly et al. (2007) stress that cash flow may also contain information on investment opportunities when there is high uncertainty about firm´s investment projects.

As it is impossible to measure marginal q correctly, this makes tests of investment cash flow sensitivity based on indirect measures imprecise in statistical terms. Another problem with average Q of Tobin is the fact that it only exists for listed firms. However, listed firms are the ones that would normally have more access to credit. In contrast to listed firms, private firms are the ones that should be more prone to depend on banks for investment.

Direct measures of financial restrictions, different from indirect measures, do not use average Q of Tobin. They are built 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. For instance, in the case of reports, Kaplan and Zingales (1997) read them, searching for expressions that are symptomatic of the presence of financial constraints.

[4] The most common way to measure size is by total assets, although some authors also use number of employees or age. In general, however, age and number of employees are highly correlated with size.

[5] There are other balance sheets or financial characteristics used in the indirect measures, such as credit ratings, or capacity firms have to give collaterals for loans, among others. See Silva and Carreira (2012) for more details.

Another possibility to create direct measures of financial restrictions is through surveys.[6] In surveys, firms are asked whether they are financially restricted or not and this can be done by a single question or combination of different questions, related to their cost of external funds, credit denials, and availability of external funds. The main advantage of surveys is that firms are the best-informed agents with respect with the quality of their projects. One should expect that investment opportunities are already considered in firm´s responses. It is also possible to measure financial restrictions for small and young firms that do not publish their balance sheets, which is not possible in the case of indirect measures. To complement survey information, one can also use quantitative information as well.

Like indirect measures, direct measures have also some downsides. The subjective nature of self-assessed variables means that potential biases resulting from management perceptions may exist. In addition, information is expensive to collect, somewhat scarce, with insufficient level of detail. It is also important to complement surveys with information coming from financial institutions, which is seldom available.

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 and cited indexes in the literature. They are built based on qualitative and quantitative information and share the advantages and disadvantages of direct and indirect measures.

We think that our paper contributes in an important way to empirical literature, because not only our measures of financial restrictions are different, but also, 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 private firms directly from their loan contracts with financial institutions. We use information of 3,469,135 loan contracts of 8,010 private firms written with banks from 2012 to 2020 and registered at System of Credit Register (hereafter SCR) of Banco Central do Brasil (hereafter BCB).

The SCR allow us to have a better comprehension of the access of credit of firms for investment. So, for example, we know that the firm is in liquidation or in bankruptcy in which

[6] See, for example, Campelo et al. (2010), Beck et al. (2008) and European´s (ECB)´s Acess to Finance Survey.

case it will be very unlikely to obtain credit for investment. SCR also informs the motive or type of the loan contract. There is information that the firm obtained credit for investment or for project financing in which case we also can deduce that the firm is not credit constrained for investment. There is also very detailed information on the maturity and interest rates of loans, among other very relevant credit information.

We classify a private firm every year of our sample in five different categories depending on its likelihood to obtain credit for investment: very likely to be financially restricted (liquidation or restructuring), likely to be financially restricted, not capable of identifying, likely not to be financially restricted and very likely not to be financially restricted (in the case the firm obtained credit for investment or project financing).

Our core measures of credit restriction classify private firms in a certain year as likely to be financially restricted or not, depending on how average interest rate and average maturity of their contracts fit in the cross-section distributions of interest rates and maturities of all loan contracts of firms written in this year with financial institutions.

We build also other measures that complement our core measures with information of private firms related to: the number of financial institutions they have relationship with; if they have loans in delinquency over 90 days; the quality of their loans portfolios; if they have outstanding foreign exchange derivatives contracts[7]; how much collateral they offer in their loan contracts; and, finally, some balance sheet characteristics such as coverage ratio, fixed assets and size (total assets).

We also think that we contribute to the literature because we study only private firms, which is also not common in the literature. Most papers that measure financial restrictions look only at listed firms, which should be much less likely to be credit constrained for investment.

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. In

[7] We use information of foreign exchange derivatives contracts, because we ponder that a firm that has access to these derivatives, either through a Mercantile Exchange or through over-the-counter contracts, is less likely to be financially constrained.

addition, given our financial restricted measures we may understand better investment cash flow sensitivity in Brazil.

Our results show that our financial restriction measures explain well access of private to credit for investment as well as indicate that their investment is negatively related to financial restrictions in Brazil. Furthermore, our results also show that credit policies of BCB had positive effect on working capital loans but did not have any effect on investment of private firms in the Covid-19 pandemic period.

Our paper is some ways related 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. This could have created a sample selection bias in our paper, due to the fact that our financial restriction measures are based on loan contracts we observe in SCR. We test for this possibility using Wooldridge (1995) test for panel data and find no statistically significant evidence of sample bias. In addition, we collect evidence of demand of investment of firms, from their balance sheet information, that gives us even more confidence of no sample selection bias in our empirical analyses.

The remainder of the paper is the following. Section 2 describes in more details the empirical literature on financial constraint measures. Section 3 describes the data. Section 4 presents our empirical identification strategy. Section 5 shows the results of the main and robustness empirical analyses. Section 6 concludes.

2. Literature Review of Financial Constraints Measures of Firms

The theoretical literature on measures of the relation between financial constraints of firms and investment is based on the relaxation of the hypothesis of perfect markets of Modigliani-Miller (1958) ´s theorem. Modigliani-Miller demonstrate that, in perfect capital markets, external finance is a perfect substitute for internal finance, thus financial structure of firms and financial policy is irrelevant for its investment decisions.

Stiglitz and Weiss (1981) and Myers and Majluf (1984) document well the consequences of capital market imperfections due to agency problems. The fundamental idea is based on the existence of moral hazard and adverse selection problems that either set the price of credit on above-optimal levels or rationalize (in some circumstances by complete) credit. This inefficiency sets a wedge between internal and external forms of firm´s financing. As a result, firm´s investment decisions will not be optimal, and they will not be able to fulfill their growth and investment optimal targets.

The problems with asymmetric information in capital markets can be more severe for small and young firms. This will happen because there is still not much information on these firms available to most potential lender. Potential lenders are not able to observe the quality of the risk or do not have control over the firm's investment. Under these conditions, smaller and younger firms are expected to be more credit constrained, as shown by Petersen and Rajan (1994, 1995).

Empirical work related to the measurement of financial restrictions and its relation to investment can be decomposed in three distinct strands, as we explained very briefly in the Introduction: indirect measures, direct measures and indexes. Indirect measures are related to the study of the sensitivity of investment to cash-flow; direct measures are based on surveys and off-balance sheet reports of firms, while indexes are based on combination of direct and indirect approaches.

To measure the sensitivity of investment to cash-flow, indirect measures use regressions based of investment as a dependent variable and average Q of Tobin and cash-flow as explanatory variables, besides separating the sample of firms in credit constrained and non-constrained firms. The null hypotheses of these tests are that cash-flow sensitivity is going to be higher for constrained firms than for unconstrained firms.

To separate, ex-ante, firms in financially restricted or not, the literature uses several balance sheet or financial characteristics such as: assets, age, number of employees, credit ratings, number of bank relationship, among some others.[8]

Average Q of Tobin is a proxy for marginal q of Tobin (1969), which measures the increase in the present value of a firm's profits resulting from a marginal increase in the firm's capital stock and is non-observable.[9] There are several ways to define average Q. One that is very common in the literature is the ratio between the market value of the firm and its cost of

[8] See Silva and Carreira (2010).

capital replacement. As this cost of capital replacement is not observable, total assets or fixed assets are often used as substitutes in the literature. A high level of Q thus would be an indication of the presence of investment opportunities. It is argued that Q (or marginal q being more precise) summarizes all future information that is relevant for a firm when deciding to invest.

A relevant setback with average Q of Tobin is the fact that it only exists for listed firms. An interesting alternative to the estimation of investment without Q of Tobin is developed in Gala et al. (2020). The authors estimate investment demand without information about market values and hence average Q of Tobin, but under general assumptions about technology and markets.

The seminal work on financial restrictions measured in indirect way is Fazari, Hubard and Petersen (1988). The authors investigate the impact of cash-flow sensitivities on investment by classifying firms in credit constrained or not according to their dividend policy. The reason for this classification rests on the argument that firms that pay low dividends, since their needs for resources for investment exceed their internal cash flow and they are credit constrained. They show using a sample consisting of 422 USA firms from 1970 to 1984 that the coefficient of cash-flow for the low-dividend group is higher and statistically different than the coefficient for the high-dividend group. This suggests that low-dividend firms invest more of their extra cash-flow than high-dividend firms.

On the other hand, Kaplan and Zingales (1997) argue that cash-flow is not a good measure of the existence of financing constraints and Fazzari, Hubbard and Petersen's (1998) a priori classification of firms is flawed. They instead classify firms according to information obtained from company annual reports and find evidence that constrained firms are the less sensitive to cash-flow. This argument is also supported by Kadapakkam et al. (1998) and Cleary (1999). Recently, Dasgupta and Sengupta (2007), for Japan, find that the response of investment to cash-flow shocks is non-monotonic, supporting Kaplan and Zingales (1997) and Cleary (1999).

[9] Hayashi (1981) demonstrates that in perfect capital markets average Q is equal to marginal q.

Alternatively, analyzing firms' demand for cash, 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 in order 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 in opportunity costs associated with present investment opportunities. As a result, only constrained firms will need to optimize their cash stocks over time in order to maximize their profits and hedge future socks by holding cash. Therefore, one can expect that estimates on the sensitivity of cash stocks to cash-flow.

Another facet of the literature points that cash-flows might contain information about 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 the USA and the UK) and bank-oriented ones (Germany for example).

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).

Campello et al. (2010) survey 1,050 chief financial officers (CFOs) in 39 countries in North America, Europe, and Asia in December 2008. They contrast the actions of firms that are financially constrained with those that are less constrained. They develop a survey-based measure of financial constraint and then study whether this constraint measure identifies meaningful cross-sectional variation in corporate behavior during the crisis.

Beck et al. (2008) examine whether financial development boosts the growth of small firms more than large firms and hence provides information on the mechanisms through which financial development fosters aggregate economic.

The ECB´s survey on the access to finance of enterprises (SAFE) provides information on the latest developments in the financial situation of enterprises, and documents trends in the need for and availability of external financing. The survey results are broken down by firm size, branch of economic activity, country, firm age, financial autonomy and ownership. The survey is conducted twice a year.

Ferrando and Mulier (2013) draw on SAFE survey of 11,886 firms in the euro area to investigate the role of firm characteristics with respect to the experience of facing financial restrictions from 2009 to 2011. Their methodology is based on nearest neighbor matching of the firms in their sample with balance sheet information of 2.3 million firms in euro area. They are capable of distinguishing perceived from actual financial obstacles and they show that more profitable firms are less likely to face actual financing constraints.

The third strand of the literature is indexes. They combine indirect and direct measures, and thus have the advantages and disadvantages of them. They have quantitative as well as qualitative information. Some of most important indexes in the literature are Kaplan and Zingales (1997) and White and Wu (2006). The Kaplan-Zingales index is a relative measurement of reliance on external financing. Companies with high index are more likely to experience difficulties when financial conditions tighten since they may have difficulty financing their ongoing operations. The index is based on a five-factor model of the following variables: cash-flow, Q of Tobin, Total Debt, dividends and Cash.

Whited and Wu's (2006) index is derived from a generalized method of moments estimation of an investment Euler equation. The LaGrange multiplier of the external financing constraint is the shadow cost of external financing. It is a function of five factors: ratio of total debt to total assets, indicator if the firm pays or not dividends, the growth of firm´s sales, the growth of the firm´s sector and cash divided by total assets.

The existence of financing constraints appears to be particularly severe for firms that decide to invest in R&D because of the risks associated with the investment. As argued before, credit markets will no longer be efficient, generating a wedge between internal and external financing faced by firms as well as a financing hierarchy. For example, Hall (1992), and Himmelberg and Petersen (1994), find support for the hypothesis that R&D investment is financially constrained for small firms. Hall et al. (1999) in a comparative study of French, Japanese and the USA firms also sustain these findings.

The financial constraints faced by firms can, obviously, have important effects on the firm's ability to stay in the market. For example, Musso and Schiavo (2008) find that, for French manufacturing firms over the period 1996-2004, the greater the financial constraints firms face, the higher the probability that they do not survive and then exit the market.

3. Data

We have two sources of data. The balance sheet and financial information of private firms (hereafter firms) come from Valorpro. [10] Valorpro has the advantage of having information mostly on medium size firms, which are our main interest in this paper. The information of firm´s loan contracts comes from SCR.

[10] Valorpro is a database of balance sheet and financial information of firms. It is a proprietary database of Brazilian economic journal *Valor Econômico*.

Our database of has unbalanced balance sheet and financial information of 8,010 firms from 2012 to 2020. There are 5,503 joint stock 2,568 limited liability firms. We classify these firms in 5 sectors, following the classification scheme of Valorpro: Agriculture, Commerce, Energy, Industry and Services. Most firms come from the services sector (4,111).

[Insert Table 1]

Table 2 Panel A displays the descriptive statistics (mean and standard deviation) of balance sheet and financial information firms in our sample. The largest ones (measured by the natural logarithm of total assets) come from the energy sector followed by the industry sector. The highest average investment (capex) occurs in services sector (10%). The most profitable sector, measured by average quotient between ebitda and total assets, is agriculture sector (1.46), and the one with the highest leverage is the energy sector (0.95). In terms of annual growth of operational revenues, on average, services sector has the highest average value 3.93%.

Table 2 Panel B shows the number of foreign exchange derivatives contracts of our database firms classified by type of derivative, long or short positions and sectors. Forward contracts are predominant, followed by option contracts. Most firms are long in the foreign exchange rate.

[Insert Table 2]

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

The SCR has flow, stock and cadastral information of these loan contracts. In case of cadastral information, SCR informs if the firm is in liquidation or in a restructuring process due to a bankruptcy process. In case of flow information, one can observe, among other features of the loan contracts, the date contract was written, interest rate charged, maturity and motive or type the loan contract, and the credit risk of the loan. Stock information, for example, relates to if loan has more than 90 days delinquency, the relative importance of bad loan in relation to the total portfolio of loans, the number of bank relationship the firms have, among other characteristics.

In our empirical identification strategy, as we will make clear in next section, we will use all the information of loan contracts mentioned above. In case of flow information, we are interested in contracts written between firms and financial institution from 2012 to 2020.

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 2014 and 2016. We conjecture that this may have happen because of a decrease in GDP growth, which had to do with deterioration of fiscal side of the economy observed in Brazil during these years.

[Insert Figure 1]

The information contained of loan contracts in SCR allows us to distinguish firms that are in liquidation or restructuring due to a bankruptcy process. Figure 2 shows the number of firms in such situations changed little in the period. This number is relatively stable throughout our sample period.

[Insert Figure 2]

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 discount of credit instrument, secure overdraft facilities, long-term working capital, short-term working capital, 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. It is not clear, however, that, in the case firms are acquiring financing loans that they are investing, that is, increasing their capital stock.

In addition, 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 3 presents the percentage of types of loans contracts of the firms in our database from 2012 to 2020. Figure 3 shows that working capital loans exceed by far loans for financing and investment or project financing in all years. It is important to note that almost all loans in 2020, in which occurred the Covid-19 pandemic (hereafter pandemic), were working capital loans. We think that this has to do with the credit policies of BCB implemented during the pandemic to mitigate its effects on financial restrictions of firms.

[Insert Figure 3]

4. Empirical Identification Strategy

4.1 Identification of Financial Restriction Measures

Our empirical identification strategy of financial restrictions measures is the following. We start by defining five categories of firm´s relative access to credit for investment. The categories are very likely non-financially restricted, likely to be financially restricted, not enough information to classify, likely to be non-financially restricted and very likely to be non-financially restricted.

Table 3 presents our financially restricted measures based on the categories above. All our measures are calculated every year, so they can change in our sample period. Our core measures presented in Table 3 Panel A are FR1_Contracts, FR2_Contracts, FR3_Contracts.[11] They are equal to 1 if the firm is in restructuring or liquidation; they are equal to 5 if the firm obtained loans for investment or project financing; they are equal to 3 if we do not have enough information to identify if they are financially restricted or not.

FR1_Contracts, FR2_Contracts and FR3_Contracts differ in the way they fall in the categories 2 or 4. For a certain firm in a certain year, FR1_Contracts is equal to 4 in two situations. In the first one, firm acquired financing loans. In the second one, firms obtained only working capital loans, in which average interest rate was lower than 30% percentile of its cross-section distribution and average maturity was higher than the 70% percentile of its cross-section distribution.

FR1_Contracts is equal to 2 if the firm acquired obtained only working capital loans and the average interest rate of these working capital loans was higher than the 70% percentile of its cross-section distribution, as well as average maturity was lower than the 30% percentile of its cross-section distribution.[12]

FR2_Contracts and FR3_contracts differ from FR1_Contracts when we classify them in categories 2 or 4, because they consider the 80% and 90% percentile respectively of the cross-section distribution of maturities instead of the 70% percentile, and because they use the 20% and 10% percentile of cross section distribution of interest rates respectively instead of 30% percentile.

We build other financial restriction measures that complement our measures above using information of firms related to the number of delinquency days of loans; the demand of foreign exchange derivatives; number of bank relationships; information of their portfolio of non-performing loans (bad loans); average collateral provided; and from some balance sheet information. All this information is relevant because they can change the classification of our core measures in category 3 (unable to identify credit restrictions) into categories 2 (likely to be restricted) or 4 (likely to be non-restricted).

Table 3 Panel B describes how these complementary measures allow us to change a firm from category 3 (not enough information) to category 2 (very likely to be constrained) in a certain year: delinquency if we observe that the firm had loans in delinquency over 90 days; a bad portfolio, one in which a firm has more than 70% of its portfolio of loans non performing; balance sheet information related to total assets, fixed assets in relation to total assets and coverage ratio, where their average is less than the 30% percentile of their respective cross-section distribution; ratio between average collateral pledged and total assets

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[11] FR is an acronym for financial restrictions.

[12] The 70% percentile and 30% percentile are thresholds adopted as a simple back-of-the-envelope rules, and are commonly used in many empirical works, see Moore et al. (2013).

is less than 30% percentile of the its cross-section distribution; finally, the number of bank relationships of firms is less than 30% percentile of its cross section distribution.

Table 3 Panel C describes other measures that allow us to change a firm from category 3 (not enough information) to category 4 (likely not to be constrained) in a certain year: good portfolio, one in which a firm has less than 30% of its portfolio of loan non performing; balance sheet information related to total assets, fixed assets in relation to total assets and coverage ratio is higher than the 30% percentile of their respective cross-section distribution; average ratio of collateral pledged to assets is higher than 70% percentile of the its cross section distribution; finally, the number of bank relationships of firms is higher than 30% percentile of its cross section distribution.

Table 3 Panel D shows that our measures of financial restrictions defined above are highly correlated. As one can observe, average correlations vary from a minimum of 0.82 to a maximum of 0.94.

[Insert Table 3]

Therefore, we have a total of 18 different measures of credit restriction of firms in our sample. To select only one that we think more appropriate, we do the following. We estimate pool of cross section ordered probit, where dependent variables are our measures of financial restrictions explained above and our explanatory variables are taken from Whited and Wu index (2006). They are ratio of total debt to total assets, growth of firm´s operational revenues, ratio of dividends to assets; and cash divided by total assets.[13]

We then select the best a-prior classification of finance restriction as the one in which the average observed probabilities of forecasting all categories of financial restriction above, except for category 3, in our ordered panel probit estimations is the highest.

After selecting the best a-prior classification, we define a firm as financially restricted in a certain year if its classification in that year is very likely (1) or likely (2) to be financially

[13] We prefer Whited and Wu (2006) index from Kaplan and Zingales (1997) index because the former does not use Q of Tobin, which is important in our empirical analyses, because we have only private firms in our database.

restricted. Otherwise, we consider a firm to be non-financially restricted if its classification falls in categories likely (4) or very likely (5) to be financially non-restricted.

4.2 Investment Demand

We use our selected financially restricted measures to estimate investment demand regressions of our unbalanced panel of firms from 2012 to 2020. We have different estimations depending on if the group is made of financially restricted or non-restricted firms.

In our main empirical analyses, we estimate Equation (1) below, using panel data and firm fixed effects. Equation (1) is based on Gala et al. (2020). Gala et al. estimate investment policy functions under general assumptions about technology and markets. 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.

The dependent variable is the ratio between capex and assets. We estimate this equation for two distinct sample of firms and two distinct sample periods. In the case of the former, we estimate for financially restricted firms (FR) and non-financially restricted firms (NFR). In the case of latter, in some estimation, we use all our sample period from 2012 to 2020 and in other ones we implement difference-in-difference (hereafter dif-in-dif) estimations related to natural exogenous shock of Covid-19 pandemic and the sample period goes from 2018 to 2020. In all estimations, we correct for heteroscedasticity.

In case of estimations of the whole sample period, in addition to a constant, our regressors are growth of operational revenues (var_oper_rev), natural logarithm of total assets (lassets) and fixed total assets (fixed_assets). [14] In case of dif-in-dif estimations, we include - in addition to the regressors of the estimations of the whole sample period - a dummy regressor, pandemic, indicating Covid-19 pandemic, equal to one in 2020 and zero in 2018 and 2019, and a regressor that is an interaction between pandemic and growth of operational revenue, pandemic*var_oper_rev. With the inclusion of this regressor, we want to verify if the credit policies of BCB in 2020 where effective for firms that we classify as financially

[14] Firm fixed effects are represented by a_i. Due to space restrictions, we do not show the estimated coefficients of constants.

restricted in the Covid-19 pandemic period. Table 4 presents a list of some of the more important credit policies of BCB for firms in 2020.

[Insert Table 4]

The null hypotheses that we want to test are- following Fazari, Hubbard and Petersen (1988)- that for the group of financially restricted firms, the coefficient (β_1) of var_oper_rev is positive, while for the group of non-financially restricted firms either this coefficient is zero or negative. Furthermore, we want to assess if credit policies of BCB during the pandemic decreased the sensitivity of investment to cash-flow, that is we want to test if the coefficient (β_4) of pandemic*var_oper_rev is negative.

$$\frac{capex_{it}}{Assets_{it-1}} = \beta_0 + \beta_1 \text{var}\_oper\_rev_{it} + \beta_2 lassets_{it} + \beta_3 fixed\_assets_{it} + \beta_4 pandemic_t * \text{var}\_oper\_rev_{it} + \beta_5 pandemic_t + a_i + u_{it} \quad (1)$$

In next section, we will present the results of our main empirical analyses and robustness exercises.

5. Results

5.1 Financial Restrictions Measures

Table 5 shows the average probabilities of the best model´s forecasts of the categories of our ordered dependent variables. The FR3_contracts_qifs is the financial restriction measure with the highest probability of fitting (0.43), followed by FR2_qifs (0.39).

[Insert Table 5]

We define a firm as financially constrained (FR) firm if it belongs to FR3_contracts_qifs categories of very likely (1) or likely (2) to be credit constrained. We define a non-financially constrained firm (NFR) if it belongs to category likely (4) or very likely (5) to be non-financially constrained. Figure 4 displays the evolution in our sample period of the number of private firms in each category of financial restriction measures based on FR3_contracts_qifs.[15] One can see that categories financially restricted (FR) non-financially restricted (NFR) are relatively stable in our sample period.

[15] FR(1 to 5) means that FR3_Contracts_qifs is equal to 1 to 5 respectively.

[Insert Figure 4]

Figure 5 shows the year average classification of financially constrained and non-financially firms in our sample period. Both series look very stable throughout the years. Figure 6 and Figure 7 show the number of financially constrained firms and non-financially restricted firms respectively classified by sectors. It is clear from both Figures, that firms of the services sector are the ones with more firms in both categories.

[Insert Figure 5]
[Insert Figure 6]

We perform mean tests of some characteristics of group of firms financially restricted or not. Table 6 shows that the group of firms that are non-financially restricted are larger and invest more than firms that are financially restricted. However, we do not see any statistically significant difference between the groups of financially restricted or not as far as profitability (ebita/assets) and growth of operational revenues are concerned (var_oper_rev).

[Insert Table 6]

5.2 Results of Estimations of Investment Functions

Table 7 displays the results of our main estimations of investment demand, Equation (1), based on Gala et al. (2020) for financially restricted and non-financially restricted firms, respectively. The results in Table 7 show that the sensitivity of investment in relation to cash-flow (measured by the coefficient of growth of operational revenue(var_oper_rev)) for financially restricted firms is positive and statistically significant and varies from a minimum of 0.0048 to a maximum of 0.013, capex_assets. Therefore a 1% increase in cash flow *ceteris paribus* would increase from a minimum of 0.4% to a maximum of 1.38% the ratio of capex to assets. The coefficients estimated of the var_oper_rev for the case non-financially restricted firms is negative and statistically significant, -0.211, or non-statistically significant.

In addition, dif-in-dif estimated regressions indicate that, in pandemic period, coefficient of the interaction between cash flow measure and pandemic, var_oper_rev*pandemic, is not statistically significant. This may point to the fact that credit policies of BCB, during the pandemic, directed towards small and medium size Brazilian firms, such as the ones we have in our sample, did not mitigate the effects of credit restrictions on investment of these firms.

In next section, we will present results of some robustness exercises to verify if the results of our main empirical analyses described above continue valid.

[Insert Table 7]

5.3 Robustness Exercises of the Estimation of Investment

The robustness exercises comprise estimations related to tests of possible selection sample bias based on Wooldridge (1995), which is an extension of Heckman (1976) two step methodology for panel data; estimation of different specifications in line with the econometric model of Gala et al. (2020); estimation of different models of investment based on Bond et al. (2003) and Eberly et al. (2012); estimations dealing with possible endogeneity of growth of operational revenues and measurement errors of financial restrictions measures.

5.3.1 Testing Sample Selection Bias

We may have a sample selection bias in our regressions presented before due to the fact that we define our financial restriction measures based mainly on loan contracts we observe in SCR. This is known as the incidental truncation problem. This is similar to estimating a wage offer equation using a panel of individuals. Even if the population of interest is those individuals who are employed in initial year, some of them will become unemployed in subsequent years. For these latter individuals, we cannot observe a wage supply, just as in the cross-sectional case.

For incidental truncation problems, it is reasonable to extend Heckman´s (1976) two step methodology to the unobserved effects panel data framework, following Wooldridge (1995). Under the null hypotheses of no sample bias selection the coefficient of inverse Mills ratio variable should not be statistically significant in second step equation estimated by panel fixed effects.

To implement Wooldrige (1995) test we use two dummy variables defined on section 5.1 above, which are FR and NFR, respectively one that indicates that a firm is financially restricted and another that indicates that a firm is not financially restricted respectively. The first equation of the two step Heckman test – for the financial restricted and non-financial restricted case- has the same regressors of our ordered regression selection pool regressions presented above, that is ratio of total debt to total assets, growth of firm´s operational revenues, ratio of dividends to assets; and cash divided by total assets.

Table 8 below presents the results of second step equation of Wooldridge (1995) test of sample bias for whole sample period, and for financially restricted and non-financially restricted firms. As one can observe, for both cases coefficient of inverse Mills ratio variable is statistically non-significant, that indicates our main empirical regressions do not suffer from sample bias.

[Insert Table 8]

5.3.1 Robustness Exercises based on Gala et al. (2020)

We estimate several regressions similar to Equation (1) above and centered on Gala et al. (2020), correcting for outliers of investment, substituting some regressors by other ones, changing the definitions of regressions and including new ones.

In Table 9, Panels A to F, we show the results of these robustness exercises: in Panel A, we restrict our sample of firms to those that have ratio of capex to assets between the 5% percentile and 95% of the cross-section distribution of this ratio every year in our sample period; in Panel B, we substitute growth of operational revenue for growth of ebitda; in Panel C, we include macroeconomic regressors, such as SELIC rate, GDP growth and Inflation[16]; in Panel D, we include dummy regressors indicating sectors of the economy (agriculture, commerce, energy, industry and services)[17]; in Panel E, we include regressors leverage and liquidity (measured by the ratio of cash to assets); in Panel F, we estimate equation (1) with the same regressors using deflated (real) values, instead of nominal ones.[18]

[16] Inflation is measured by "Índice de Preços ao Consumidor Ampliado" (hereafter IPCA).
[17] In the case of these regressions, we use between effects instead of fixed effects.

The results displayed in Table 9 Panels A to F confirm those we obtain in our main empirical analyses, that is, the elasticity of investment in relation to cash-flow for financially restricted firms is positive and statistically significant, and negative or statistically non-significant for the case non-financially restricted firms. In addition, in most dif-in-dif estimated regressions, the coefficient of the interaction between cash flow measure and pandemic, is not statistically significant.

[Insert Table 9]

5.3.2 Different Investment Specifications: Vector Error Correction and Lagged Investment

We estimate, using Arellano-Bond (1991), investment demand functions taking in consideration lagged investment effect (one lag of investment as one of the regressors) based on Eberly et al. (2012). The authors show that the best predictor of current investment at the firm level is lagged investment. In their view, lagged-investment effect is empirically more important than the cash-flow and Q effects combined.

We also estimate a vector error correction model of investment (see Bond et al. (2003)), where there is an error correction vector of operational revenues and fixed assets lagged two periods. Bond et al. construct company panel data sets for manufacturing firms in Belgium, France, Germany, and the United Kingdom, covering the period 1978-1989. They use these data to estimate empirical investment equations, and to investigate the role played by financial factors in each country.

The results presented in Table 10 for Eberly et al. (2012) and Table 11 for Bond et al. (2003) models, once more, endorse the ones of our main empirical analyses. [19]

[Insert Table 10]

[Insert Table 11]

[18] To deflate nominal values we use price index IPCA.

[19] In the case of the Bond et al. (2003) model, the coefficient of var_rev_oper is not statistically significant for firms with financial restrictions and, in accordance with our null hypothesis, negative and statistically significant for firms with no financial restrictions.

5.3.3 Endogeneity

In a fourth attempt to verify the robustness of our main empirical results, we contemplate possible endogeneity of the regressor growth of operational revenues in the estimation of Equation (1). We perform two different econometric exercises to deal with this possibility. In the first one, we estimate Equation (1) using two stages least squares (hereafter 2SLS) with the first lag of growth of operational revenue as an instrument.[20] The results shown in Table 11 Panel A confirm once more our main empirical results

In the second econometric exercise, we implement Average Treatment Effects (hereafter ATE) estimations based on Nearest Neighbor Matching (hereafter NN) and Propensity Matching Score (hereafter PMS). In the case of NN, the treatment variable is a dummy variable that indicates a firm is financially restricted (FR), matching variable is natural logarithm of assets and the regression is identical to Equation (1). In the case of PMS, the matching is based on a regression of a dummy that indicates financial restriction, FR, with respect to the same regressors we use in the selection of the best financial restriction measure based on White and Wu (2006) [21] and the regression specification is the same as Equation (1).

The results of our estimations - which deal with possible endogeneity of growth of operational revenues - are presented in Table 12 Panels A and B. As one can observe, the coefficients estimated in 2SLQ estimations confirm our main empirical analyses results. In the case of the ATE estimations, one can see that the ATE of the ratio of capex to assets is negative and statistically significant in NN estimation for the pandemic period. In other estimations, ATE sign is also negative but not statistically significant.

[Insert Table 12]

5.3.4 Errors of Financial Restriction Measures

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

[20] We test other instruments. However, Haussman (1978) test of specification rejects all estimations with more lags in favor of regression with one lag of growth of growth of operational revenue as an instrument.
[21] See the data section of this paper.

questioned in several manners. It can be wrong, or it may not describe all the possibilities in which firms could be subject to financial constraints.

To handle possible measurement errors, we implement two distinct set of exercises. In the first set, we analyze in details the group of firms that we were unable to classify into more likely or less likely to be financially constraint due to lack of information, that is, firms in category 3 of our chosen financially restricted measure. In second set of exercises, we estimate semi-parametric models based on Klein and Spady (1993), where dependent variables are dummies indicating financial restrictions (equal to one) or not (equal to zero) of firms, depending on our measures of financial restrictions presented earlier in the paper. [22]

5.3.4.1 Sample of Firms with not enough information to know its credit status

Firms in category 3 of FR3_contracts_qifs (our chosen measure of financial restrictions) are the ones in which the data that we have does not allow us to observe some characteristics that would lead us to classify them in either the category likely to be financially constrained or likely to be non-financially constrained. Firms in these situations could be the ones where there are not investment opportunities available, or those that our database of loan contracts from SCR are unable to give us an understanding of how they finance their investment.

Figure 8 describes the number of firms that we cannot discriminate into some degree of financially restricted or not. The services sector is by far the sector with more firms of this kind in our sample. It is interesting to note that the number of firms in this category increases overtime, which does not happen to firms in other sectors, whose numbers show a stable dynamic or a decreasing trend. In the pandemic period, in 2020, there is a clear increase in the number of firms of service sector in category 3. Considering that services sector in Brazil (and worldwide) was the one that suffered the most with the pandemic in terms of growth, to us this seems to be a first and important evidence towards considering firms in category 3 as those with very few investment opportunities.

[22] Hausman et al. (1988) show that misclassification of dependent variables in a discrete-response model causes inconsistent coefficient estimates when traditional estimation techniques, such as probit or logit, are used. used. One of their suggestions to solve this problem is to use semi-parametric models, such as Klein and Spady (1993).

In addition, Figure 9 shows the percentage of firms in category 3 that have capex higher than zero in our sample period. As one can easily see, very few firms in this category invest in our sample period, which is further indication these firms may be experiencing few incentives to invest.

Figure 10 corroborates, in our view, our understanding- based on Figures 8 and 9- of few investment opportunities for firms in category 3. It shows number of firms in this category separated in the following manner: those that have capex greater than zero only; those that have operational revenues greater than zero only; those that have cash and operational revenues greater than zero at the same time-but not capex greater than zero- and, finally, those that have capex and operational revenues greater than zero at the same time- but not cash greater than zero.

Two observations are striking in Figure 10: there are very few firms that have capex greater than zero only relative to ones that have operational revenues only greater than zero; there are very few firms that have capex and operational revenues greater than zero at same time in relation to those that have operational revenues and cash greater than zero at the same time. The two observations put together are, in our opinion, *prima facie* evidence that the firms in our sample are hoarding cash instead of investing, and this is probably due to lack of good projects to invest in.

Therefore, evidence presented in Figures 8 to 10 lead us to conclude that we are not able to identify firms in category 3 of our chosen financial restriction measure because these firms are not, probably, demanding investment, therefore not needing credit from financial institutions for this purpose.

[Insert Figure 8]
[Insert Figure 9]
[Insert Figure 10]

To try to reinforce our conclusions mentioned above, we create a new measure of financially restricted firms for some firms that fall in category 3. This new measured is applied to those firms that have capex and operational revenues - but not cash- greater than zero at the same time. Thus, we are suggesting that they use operational revenues to invest, instead of asking for bank credit, that is, they are more likely to be financially constrained. Then we estimate equation (1) for the whole sample and for the pandemic period once more only for firms that fit in this situation. If there was evidence that these firms were financially constrained then we would observe a positive and statistically significant coefficient of growth of operational revenues, in line with Fazzari, Hubbard and Petersen (1988). As results presented in Table 13 show coefficients estimated are negative and non-statistically significant, which points, again, to our understanding that available information on firms of category 3 do not make it possible to identify them in more or less likely to be financially restricted or not.

[Insert Table 13]

5.3.4.2 Semi-parametric estimation of Klein and Spady (1993)

The other set of exercises we perform to verify if there are error measurements in our definitions of financial restrictions is grounded on semi-parametric regressions based on Klein and Spady (1993). The authors implement an estimator for a semi-parametric binary choice model. The distribution function of error of the regression is unknown and estimated nonparametrically by kernel or local linear regression using the quartic kernel. The Klein and Spady estimator can only identify coefficients up to location and scale, so the one of the coefficients is normalized to 1. The bandwidth is computed by Silverman's (1986) rule.

To perform Klein and Spady (1993) regressions with our financial measures, we define correspondent measures of financial restrictions of these measures – one if the firm is in liquidation or restructuring (category 1) or is very likely to be financially restricted (category 2) and zero in case the firms is unlikely (category 4) or very unlikely (category 5) to be financially constrained. We use the same regressors we use in our ordered probit regressions, shown in section 4. We are interested in measuring the mean squared errors (hereafter MSE) of the difference between observed and predicted dependent variables of the estimations for every measure of financial restrictions. Table 14 exhibits the values of MSE and as one can easily see they are very small ones (all of them are lower than 10%), which is another evidence that our financial restrictions measures are less likely to have measurement errors.

[Insert Table 14]

6. Conclusion

In this paper, we build original financial restriction measures. We use these measures to have an idea of financial restrictions of 8,071 firms in Brazil from 2012 to 2020. To build these measures, we use microdata of 3,469,135 loan contracts written between these 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 is negatively related to the degree of their financial restrictions. Moreover, our results show that this did not change during the pandemic, despite efforts of BCB to relax credit restrictions of these firms in this period.

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 the literature so far. As far as we known, 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.

Future research could expand the number of private firms to be studied, which depends, of course, on the availability of detailed balance sheet and financial information of private joint stock firms and limited liabilities ones. Future research 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 of firms has unbalanced balance sheet and financial information of 5,503 joint stock private firms and 2,568 limited liabilities private firms from 2012 to 2020. We classify these firms in 5 sectors, following the classification of Valorpro: Agriculture, Commerce, Energy, Industry and Services.

Sectors	Joint Stock	Limited Liability	Total
Agriculture	179	16	195
Commerce	573	217	790
Energy	778	218	996
Industry	1,358	621	1,979
Services	2,615	1,496	4,111
Total	5,503	2,568	8,071

Table 2 Descriptive Statistics

Our database of firms has unbalanced balance sheet and financial information of 5,503 joint stock private firms and 2,568 limited liabilities private firms from 2012 to 2020. We classify these firms in 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 the number and type of foreign exchange derivatives contracts outstanding from 2012 to 2020 separated by sectors of the economy.

Panel A Mean and Standard Deviation Private Firms

	Agriculture	Commerce	Energy	Industry	Services
logassets	4.1977	3.8509	4.4828	4.1586	4.1088
	0.8640	0.8897	0.7940	0.9078	0.8980
capex/assets	0.0581	0.0427	0.0617	0.0256	0.1009
	0.2075	0.0961	0.8859	0.1208	3.2642
ebitda/assets	1.4633	1.1858	1.0119	0.8821	1.3840
	8.4061	7.4990	9.9141	27.6390	32.6111
rev_oper/assets	0.0439	0.0473	0.0727	0.0437	0.0958
	0.1296	0.1580	0.4915	0.2330	9.9161
var_oper_rev	-0.5465	0.2640	-3.4688	0.5434	3.9330
	32.7163	12.9743	224.4119	110.5750	312.5313
leverage	0.8257	0.7470	0.9571	0.9389	0.6182
	0.5624	0.6083	0.5617	0.5119	0.5915

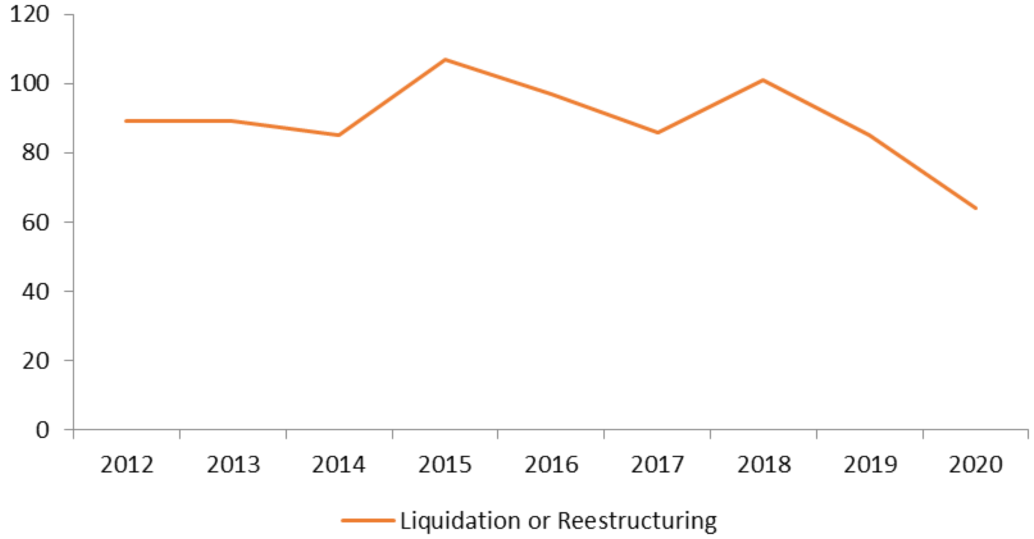
Panel B Number and Types of Foreign Exchange Derivatives Contracts

	Forward		Options		Swap		Future	
	Long	Short	Long	Short	Long	Short	Long	Short
Agriculture	5,165	6,857	86	102	241	92	0	0
Commerce	41,106	43,632	773	609	2,941	426	7,739	7,684
Energy	6,863	9,732	512	523	1,550	300	0	0
Industry	19,320	21,013	11,598	10,534	2,599	1,276	0	0
Services	4,724	1,822	173	98	1,529	127	0	0
Total	77,178	83,056	13,142	11,866	8,860	2,221	7,739	7,684

Figure 1 Number of Loan Contracts of Firms

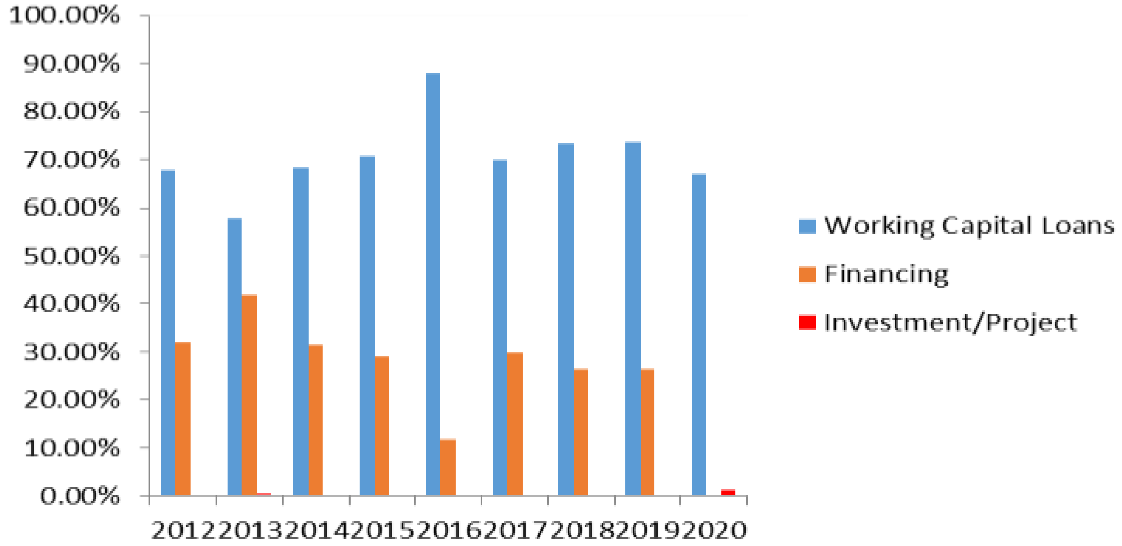
Source: Banco Central do Brasil (BCB) –System of Credit Information (SCR)

Figure 2 Number of Firms in Liquidation or Restructuring



Source: Banco Central do Brasil (BCB) –System of Credit Information (SCR)

Figure 3 Percentages of Types of Loans Contracts of Firms



Source: Banco Central do Brasil (BCB) –System of Credit Information (SCR)

Table 3 Financial Restriction Measures and Categories of Financial Restrictions

All our measures are calculated every year, so they can change in our sample period. Our core measures presented in Table 3 Panel A are FR1_Contracts, FR2_Contracts, FR3_Contracts. We build other financial restriction measures that complement these measures using information of firms related to the number of delinquency days of their of loans; the demand of foreign exchange derivatives; number of bank relationships; information of portfolio of non-performing loans (bad loans); from average collateral provided; and from some balance sheet information. Panels B and C show financial restriction measures that complement those in Panel A. Panel D shows average correlations between our financial restriction measures.

Panel A Core Financial Restriction Measures

FR1(2)[3]_contracts	Categories	Definitions
1	Very Likely Financial Restricted	Information on Reestructuring or Liquidation
5	Very Unlikely to be Financially Restricted	Investment or Project Financing
2	Likely to be Financially Restricted	Only "Working Capital" and Average Interest Rate>70%(80%)[90%] percentil and average maturity lower than 30%(20%)[10%] percentil
4	Unlikely to be Financially Restricted	Financing and Average Interest Rate<30%(20%)[10%] percentil and average maturity higher than 70%(80%)[90%] percentil
3	Not Clear	Not sufficient information to classify

Panel B Extensions of Core Financial Restriction Measures: From not enough information (3) to likely (2) to be financially restricted

3-->2	Name
Loans 90 days delinquency	FR1(2)[3]_contracts_delinquency
>70% of portfolio of loans classified as bad loans	FR1(2)[3]_contracts_bad_portfolio
assets<30% percentil and interest coverage<30% percentile and fixed assets/Assets<30% percentile	FR1(2)[3]_contracts_balancesheet
number of financial institutions relationships<30% percentile	FR1(2)[3]_contracts_qifs
average colateral/assets<30% percentile	FR1(2)[3]_contracts_collateral

Panel C Extensions of Core Financial Restriction Measures: From not enough information(3) to unlikely(4) to be financially restricted

3-->4	Name
Outstanding Derivatives Contracts	FR1(2)[3]_contracts_derivatives
<30% of portfolio of loans classified as bad loans	FR1(2)[3]_contracts_portfolio
assets>30% percentil and interest coverage>30% percentile and fixed assets/Assets>30% percentile	FR1(2)[3]_contracts_balancesheet
number of financial institutions relationships>70% percentile	FR1(2)[3]_contracts_qifs
average colateral/assets>70% percentile	FR1(2)[3]_contracts_collateral

Panel D Correlations between Financial Restriction Measures

	FR1s	FR2s	FR3s
FR1s	0.94		
FR2s	0.88	0.92	
FR3s	0.83	0.82	0.90

Table 4 Some Important Credit Policies of Banco Central do Brasil during Covid-19 Pandemic (2020)

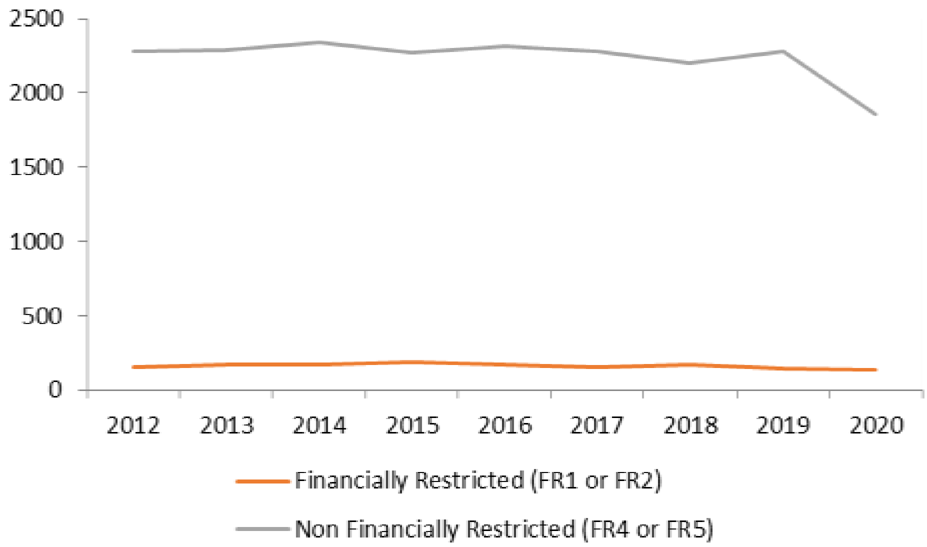
Working capital programs to preserve business continuity (CGPE)
Purchase of private securities by BCB in the secondary market
Deduction on reserve requirement on savings deposits conditional on credit provisionto mic
Real estate may be used as collateral in more than one credit operation
Emergency program provides payroll financing to SME in order to preserve employment in
Fostering credit for small and medium-size entreprises
Relaxed provisions rules for refinancing loans of SME for six months

Table 5 Selection of Financial Restriction Measures

We estimate ordered probit panels, where the dependent variables are measures of financial restrictions and explanatory variables are taken from Whited and Wu index (2006). The explanatory variables are ratio of total debt to total assets, growth of firm´s sales, ratio of dividends to assets; and cash divided by total assets.

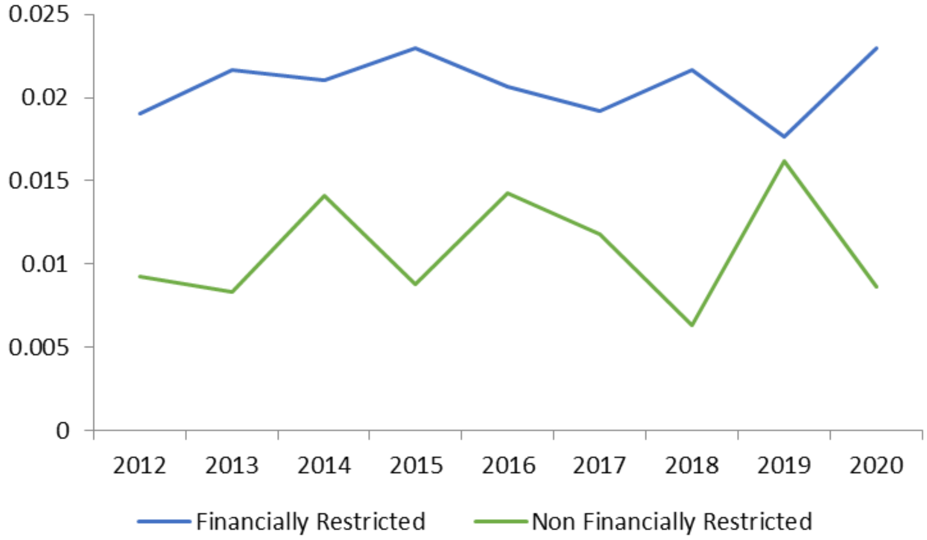
FR	Average Prob (FR=1 or 2 or 4 or 5)
Fr3_contracts_qifs	0.43
Fr2_contracts_qifs	0.39
Fr1_contracts_qifs	0.38

Figure 4 Numbers of Financial Restricted and Non-Financially Restricted Firms



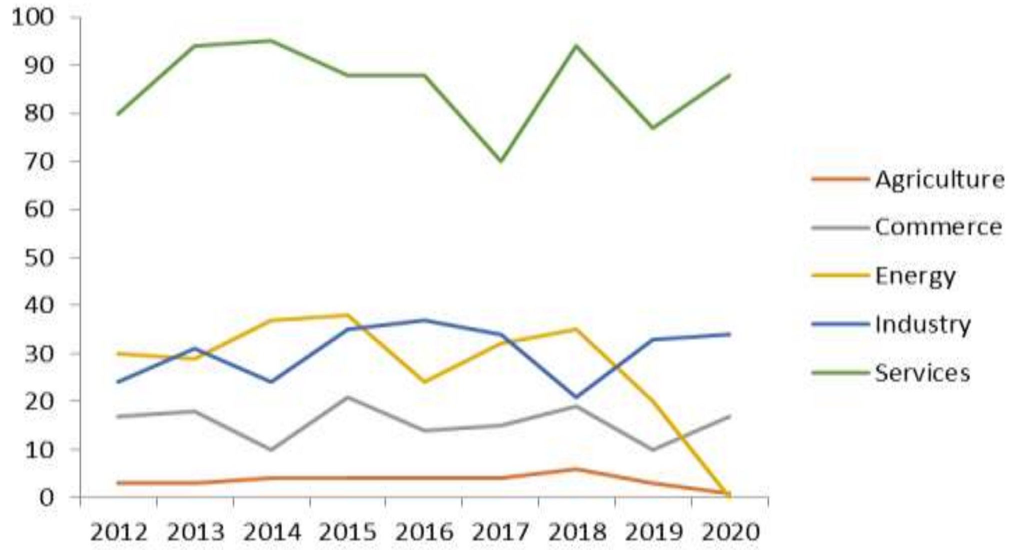
Source: Banco Central do Brasil(BCB) –System of Credit Information (SCR) and Author

Figure 5 Average Financially Restricted (FR) and Non-Financially Restricted (NFR) Firms



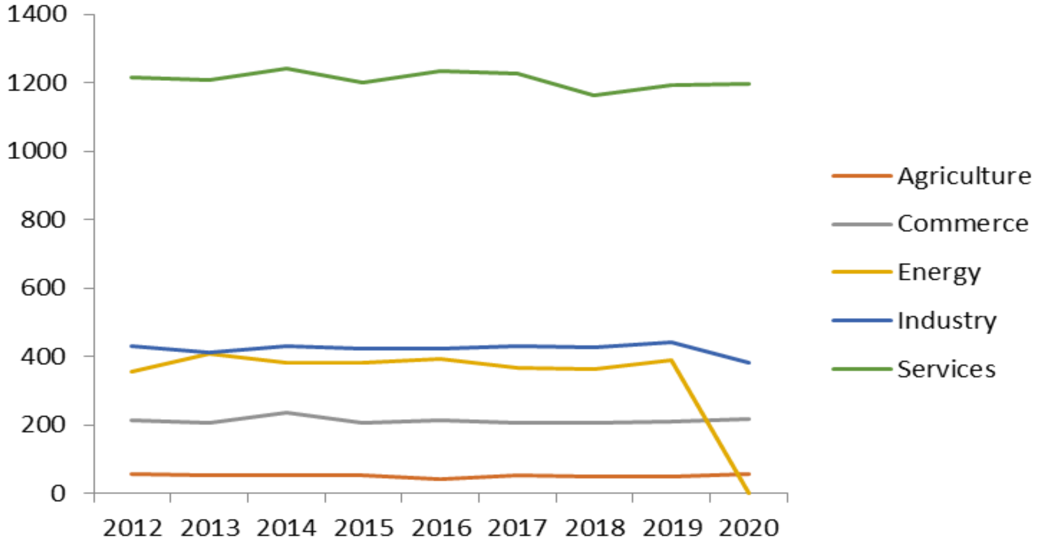
Source: Banco Central do Brasil (BCB) –System of Credit Information (SCR) and Author

Figure 6 Number of Financial Restricted Firms and Sectors of the Economy



Source: Banco Central do Brasil (BCB) –System of Credit Information (SCR) and Author

Figure 7 Number of Non-Financially Restricted Firms and Sectors of the Economy



Source: Banco Central do Brasil (BCB) –System of Credit Information (SCR) and Author

Table 6 Mean Tests of Difference in Characteristics of Financially Restricted and Non-Financially Restricted

	(FR=1-FR=0)
logassets	-0.2119***
capex_assets	-0.5500***
ebitda/assets	1.3883
var_oper_rev	0.2385

Table 7 Main Investment Demand Estimations: Based on Gala et al. (2020)
We estimate Equation (1) in the text, using panel data and firm fixed effects. Equation (1) is based on 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. FR means financial restrictions, while NFR means no financial restrictions.

	(Capex/Assets)			
	FR	NFR	FR	NFR
var_oper_rev	0.0048***	-0.211***	0.0138	-0.000
	(3.4994)	(-13.46)	(2.1207)	(-0.407)
lassets	0.0074	-0.908**	0.0016	-0.006
	(0.7242)	(-2.060)	(0.1619)	(-1.979)
imob_assets	0.1012	-0.608	0.0431	0.0742
	(0.9559)	(-1.390)	(1.5766)	(4.0823)
pandemic*var_oper_rev			0.0019	-0.000
			(0.1438)	(-1.358)
pandemic			-0.036	-0.006
			(-2.807)	(-0.925)
Robust Covariance	yes	yes	yes	no
Fixed Effects	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
N	213	1435	84	651
R2	0.029	0.93	0.16	0.17

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Table 8 Testing for Sample Selection Bias in Panel Data

We extend Heckman´s (1976) two step methodology to the unobserved effects panel data framework, following Wooldridge (1995). To implement Wooldrige´s test we use two dummy variables defined which are FR and NFR, respectively one that indicates that a firm is financially restricted and another that indicates that a firm is not financially restricted. The first equation of the two step Heckman test – for the financial restricted and non-financial restricted case- has the same regressors of our ordered regression selection pool regression presented, that is ratio of total debt to total assets, growth of firm´s sales, ratio of dividends to assets; and cash divided by total assets. We only show below the results of the second stage.

	(Capex/Assets)			
	FR	NFR	FR	NFR
var_oper_rev	-0.015	-0.211***	0.0001	0.0022
	(-0.68)	(-13.46)	(0.16)	(0.49)
lativo	-0.041	-0.908**	0.019	0.02
	(-1.29)	(-2.060)	(0.36)	(0.018)
imob_assets	0.056	-0.608	-0.019	-0.095*
	(0.21)	(-0,25)		(-1.92)
Mills	0.044	0.0049	0.63	0.815
	(0.06)	(0.81)	(0.607)	(0.175)
pandemic*var_oper_rev			0.03	-0.004
			(0.57)	(-0.81)
pandemic			-0.007	-0.0072
			(-0.12)	(-0.24)
Robust Covariance(cluster sectors)	yes	yes	yes	no
Fixed Effects	yes	yes	yes	yes
N	11,716	9,055	9,055	2,974

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Table 9 Robustness Exercises of Investment Demand Estimations: Based on Gala et al. (2020)

We estimate several regressions like Equation (1) above and centered on Gala et al. (2020), correcting for outliers of investment, substituting some regressors by other ones, changing their definitions and including new regressors. FR means financial restrictions, while NFR means no financial restrictions.

Panel A Excluding Outliers of Capex/Assets

	(Capex/Assets)			
	FR	NFR	FR	NFR
var_oper_rev	0.0048***	-0.000*	0.0125*	6.0617
	(3.4990)	(-1.817)	(1.8985)	(0.2511)
lassets	0.0074	-0.000	-0.000	-0.002
	(0.7241)	(-0.031)	(-0.069)	(-1.140)
imob_assets	0.1012	-0.126***	0.0291	0.0415***
	(0.9558)	(-5.930)	(1.2563)	(4.1004)
pandemic*var_oper_rev			0.0019	-0.000*
			(0.1472)	(-1.853)
pandemic			-0.030***	-0.006
			(-2.685)	(-1.493)
Robust Covariance	yes	yes	yes	yes
Fixed Effects	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
N	210	1417	83	639
R2	0.029	0.023	0.16	0.056

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Panel B Substituting Growth of Operational Revenues for Growth of Ebitda

	(Capex/Assets)			
	FR	NFR	FR	NFR
var_ebitda	92.455***	0.0002	-0.000	-3.536
	(4.2789)	(0.9823)	(-0.059)	(-0.096)
lassets	0.0430**	-5.188	0.0068	-0.008**
	(2.4855)	(-1.461)	(0.7111)	(-2.450)
imob_assets	0.0907	1.8470***	0.0319	0.0728***
	(0.8991)	(3.0275)	(1.1043)	(3.9640)
pandemic*var_oper_rev			0.0163	-0.000*
			(1.2172)	(-1.867)
pandemic			-0.036	-0.007
			(-2.543)	(-0.959)
Robust Covariance	yes	yes	yes	yes
Fixed Effects	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
N	210	1417	80	602
R2	0.029	0.023	0.67	0.52

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Panel C Including Macroeconomic Regressors: SELIC, GDP and Inflation

	(Capex/Assets)			
	FR	NFR	FR	NFR
var_oper_rev	0.0022*	-0.198***	0.0123*	-4.498
	(1.6415)	(-12.94)	(2.4944)	(-0.014)
lassets	-0.002	-0.335***	0.0094	0.0005
	(-0.302)	(-8.963)	(1.0660)	(0.1720)
imob_assets	0.0597	0.2329	0.0631**	0.091***
	(0.8705)	(0.7190)	(2.5548)	(4.5999)
pandemic*var_oper_rev			0.0067	-0.000
			(0.5356)	(-1.314)
pandemic			-0.034***	-0.016
			(-2.765)	(-2.073)
Macroeconomic variables: GDP, Inflation and SELIC	yes	yes	yes	yes
Robust Covariance	yes	yes	yes	yes
Fixed Effects	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
N	198	1318	84	651
R2	0.067	0.078	0.47	0.12

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Panel D Including Regressors Indicating Sectors

	Hedge (Capex/Assets)			
	FR	NFR	FR	NFR
var_oper_rev	0.0048	-0.211**	-4.498	-4.498
	(0.8592)	(-2.138)	(-0.016)	(-0.010)
lassets	0.0074	-0.908*	0.0005	0.0005
	(0.4045)	(-1.742)	(0.1870)	(0.1844)
imob_assets	0.1012	-0.608	0.0912***	0.0912
	(0.4807)	(-1.423)	(4.4628)	(4.5473)
pandemic*var_oper_rev			-0.000	-0.000
			(-0.517)	(-0.510)
pandemic			-0.016**	-0.016
			(-2.176)	(-2.016)
Sectors	yes	yes	yes	yes
Robust Covariance	yes	yes	yes	yes
Between Fixed Effects	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
N	213	1435	84	651
R2	0.029	0.93	0.22	0.08

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Panel E Using Deflated Values Instead of Nominal Values

	Capex/Assets	
	FR	NFR
var_oper_rev	0.0054***	-0.211***
	(4.1072)	(-13.45)
lassets	0.0063	-0.907**
	(0.6224)	(-2.058)
imob_assets	0.1017	-0.617
	(0.9556)	(-1.412)
Robust Covariance	yes	yes
Fixed Effects	yes	yes
Sample Period	2012-2020	2012-2020
Dif-in-Dif	no	no
N	213	1435
R2	0.03	0.93

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Panel F Including Regressors Leverage and Liquidity

	(Capex/Assets)			
	FR	NFR	FR	NFR
var_oper_rev	0.0033**	-0.220***	0.0093	-8.716
	(2.1138)	(-30.08)	(1.6032)	(-0.347)
lassets	0.0130	-0.167	0.0018	-0.007
	(1.1093)	(-0.973)	(0.1780)	(-2.106)
imob_assets	0.1102	-0.475	0.0273	0.0753***
	(1.2590)	(-0.918)	(0.9618)	(4.0570)
pandemic*var_oper_rev			-0.008	-0.000
			(-1.477)	(-0.850)
pandemic			-0.038	-0.005
			(-3.054)	(-0.738)
Robust Covariance	yes	yes	yes	yes
Fixed Effects	yes	yes	yes	yes
Leverage and Liquidity	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
N	207	1407	80	630
R2	0.065	0.96	0.10	0.07

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Table 10 Investment Demand Estimations: Lagged Effects Based on Eberly et al. (2012)
We estimate, using Arellano-Bond (1991), investment demand functions taking in consideration lagged investment effect (one lag of investment as a regressor) based on Eberly et al. (2012). FR means financial restrictions, while NFR means no financial restrictions.

	(Capex/Assets)			
	FR	NFR	FR	NFR
capex_assets(-1)	-0.087	-0.005	0.3525*	-0.029**
	(-0.27)	(-0.688)	(1.8040)	(-2.442)
var_oper_rev	0.0003**	-0.217***	0.0162***	-0.00001
	(2.2575)	(-15.01)	(3.5393)	(-0.334)
lativo	-0.024**	0.1991	0.0068	-0.009*
	(-2.090)	(0.4309)	(0.5865)	(-1.676)
imob_assets	-0.440	-0.384	0.0501	0.0711***
	(-1.586)	(-0.444)	(1.5258)	(3.6965)
pandemic*var_rec			0.0240	-0.0001
			(1.1936)	(-0.482)
pandemic			-0.057***	-0.029**
			(-2.886)	(-2.442)
Robust Covariance	yes	yes	yes	no
Arellano-Bond	yes	yes	yes	yes
Fixed Effects	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
J Statistic	19.79	28.80	23.80	24.79
N	213	1435	52	407

t statistics under parentheses

*p<0.10 **p<0.05 ***p<0.001

Table 11 Investment Demand Estimations based on Bond et al. (2003)

We estimate a vector error correction model of investment based on Bond et al. (2003), where there is an error correction vector of sales and fixed assets lagged two periods, oper_rev-fixex(-2) in addition to the regressors of our main specification Equation (1). FR means financial restrictions, while NFR means no financial restrictions.

	capex_assets	
	FR	NFR
capex_assets(-1)	-0.745	-0.006
	(-1.629)	(-1.173)
var_oper_rev	-0.000	-0.213***
	(-0.174)	(-17.89)
lassets	-0.010	-0.006
	(-0.304)	(1.6130)
imob_assets	-0.010	-0.983***
	-0.35	(-2.92)
var_oper-fixed(-2)	-0.010	7.5E-10***
	(-0.16)	(4.93)
Robust Covariance	yes	yes
Arellano-Bond	yes	yes
Sample Period	2012-2020	2012-2020
Fixed Effects	yes	yes
N	86	666
J Statistic	38.6	26.04

.

Table 12 Investment Demand Estimations: Taking in Consideration Endogeneity

In Panel A, we show the estimation of Equation (1) using 2SLS with the first lag of growth of operational revenue as an instrument. In Panel B, we display the results of Average Treatment Effects estimations based on Nearest Neighbor Matching (NN) and Propensity Matching Score (PMS). In the case of NN, the treatment variable is a dummy variable that indicates a firm is financially restricted (FR), the matching variable is natural logarithm of assets, and the regression is identical to Equation (1). In the case of PMS, the matching is based on a regression of a dummy that indicates financial restriction, FR, with respect to the same regressors we use in the selection of the best financial restriction measure based on White and Wu (2006) and the regression specification is the same as Equation (1).

Panel A Lag of growth of operational revenue as instrument

	(Capex/Assets)			
	FR	NFR	FR	NFR
var_oper_rev	0.0048***	-0.211***	0.0200***	-0.000
	(3.4994)	(-13.46)	(3.4662)	(-0.604)
lativo	0.0074	-0.908**	0.0055	-0.007
	(0.7242)	(-2.060)	(0.0142)	(-1.429)
imob_assets	0.1012	-0.608	0.0886**	0.0927***
	(0.9559)	(-1.390)	(2.2838)	(5.1567)
pandemic*var_oper_rev			-0.000767	-0.00027
			(-0.043)	(-0.230)
pandemic			-0.06603***	-0.02869***
			(-2.915)	(-2.366)
pandemic*var_oper_rev+var_oper_rev			0.0019	-0.0009
			(1.1659)	(-1.48)
Robust Covariance(cluster sectors)	yes	yes	yes	no
Instruments	var_rev_oper(-1)	var_rev_oper(-1)	var_rev_oper(-1)	var_rev_oper(-1)
Fixed Effects	yes	yes	yes	yes
Sample Period	2012-2020	2012-2020	2018-2020	2018-2020
Dif-in-Dif	no	no	yes	yes
N	213	1435	52	407
R2	0.029	0.93	0.92	0.0012

Panel B Average Treatment Effects

	ATE Capex/Assets	
	FR=1-FR=0	(FR=1-FR=0)
Nearest Neighbour Matching	-0.13	-0.016*
	(-1.03)	(-1.71)
Propensity Matching Score	-0.14	-0.0079
	(-1.06)	(-0.81)
Pandemic	No	Yes
OBS	1544	188
Number of Matches	2	2

*p<0.10 ** p<0.05 *** p<0.001

Figure 8 Number of Firms in Category 3

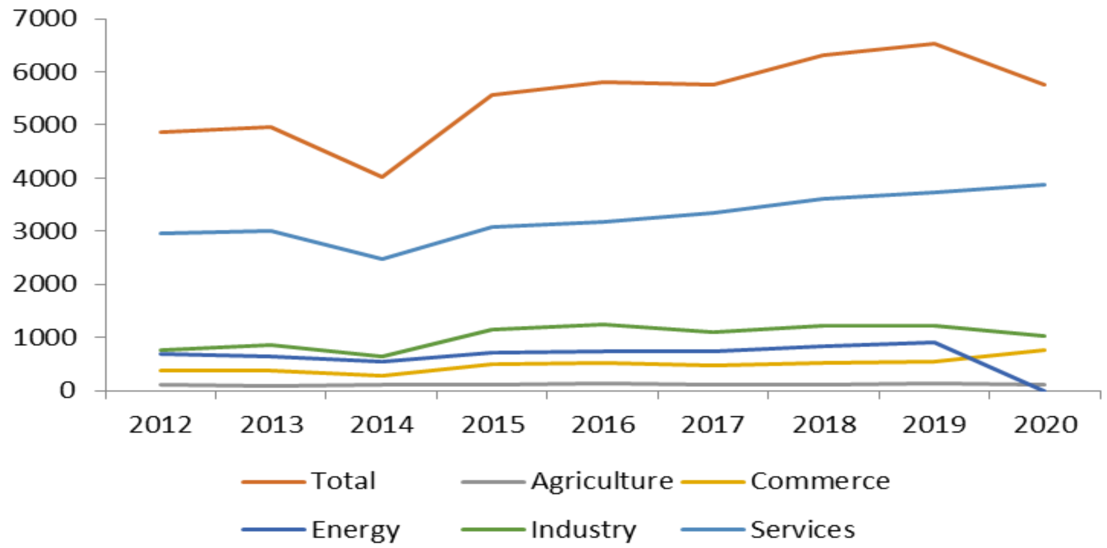
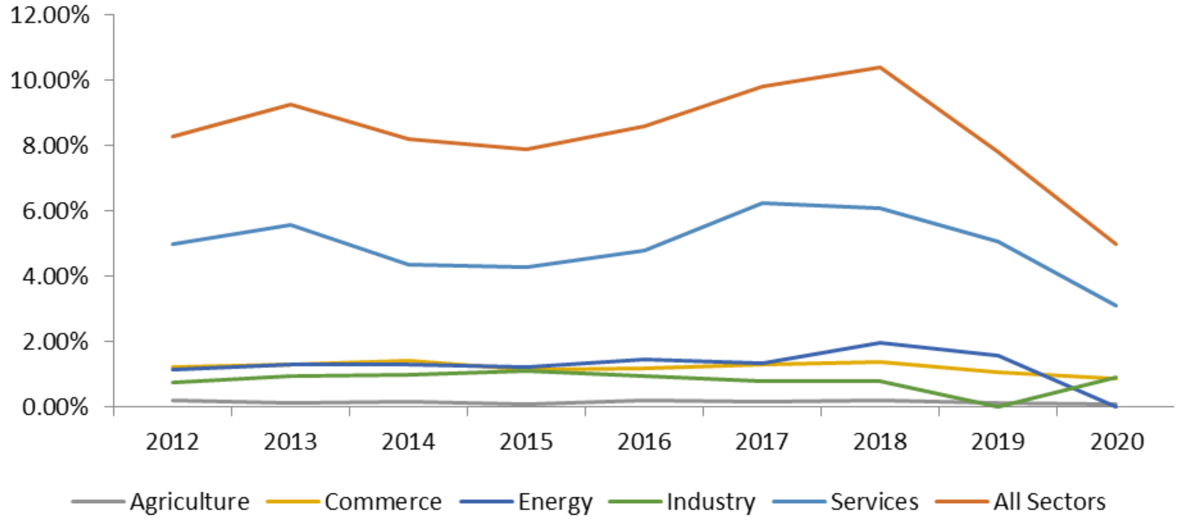
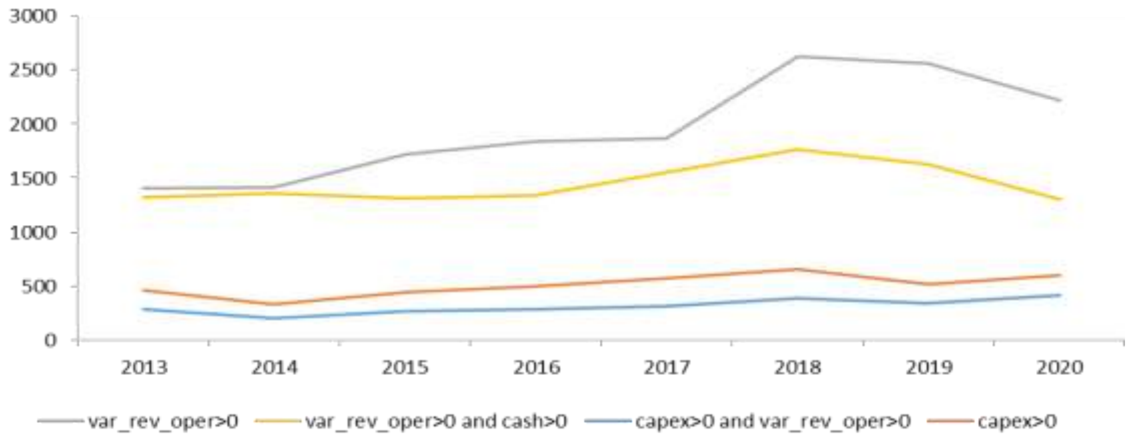


Figure 9 Percentage of Firms in Category 3 with Capex Higher than Zero Separated by Sectors of the Economy



Source: Banco Central do Brasil(BCB) –System of Credit Information (SCR) and Author

Figure 10 Number of Firms Considering Capex, Cash and Growth of Operational Revenues Greater Than Zero



Source: Banco Central do Brasil (BCB) –System of Credit Information (SCR) and Author

Table 13 Financial Restriction Estimation Including Firms in Category 3 With Capex and Growth of Operational Revenues Greater Than Zero

We estimate Equation (1) in the text, using panel data and firm fixed effects only for firms in category 3 with capex and growth of operational revenue greater than zero. Equation (1) is based on 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. FR means financial restrictions, while NFR means no financial restrictions.

	(Capex/Assets)	
	FR	FR
var_oper_rev	-9.291	-8.349
	(-0.030)	(-0.058)
lativo	-0.041	0.0098
	(-1.613)	(1.5249)
imob_assets	-0.599***	0.1598
	(-1.730)	(4.6589)
Robust Covariance(cluster sectors)	yes	yes
Fixed Effects	yes	yes
Sample Period	2012-2020	2018-2020
dif-indif	no	yes
N	489	219
R2	0.08	0.26

t statistics under parentheses

*p<0.10 ** p<0.05 *** p<0.001

Table 14 Considering Misclassification of Measures of Financial Restrictions: Klein and Spady (1993)

We estimate semi-parametric regressions based on Klein and Spady (1993). The authors implement an estimator for a semi-parametric binary choice model. The distribution function of error of the regression is unknown and estimated non parametrically by kernel or local linear regression using the Quartic kernel. The Klein and Spady estimator can only identify coefficients up to location and scale, so the one of the coefficients is normalized to one. The bandwidth is computed by Silverman's (1986) rule. We obtain mean squared errors (MSE) of the difference between observed and predicted dependent variables.

Measures of Financial Restrictions	MSE
FR1_contracts	0.07068
FR2_contracts	0.00011
FR3_contracts	0.00129
FR1_contracts_derivatives	0.06887
FR2_contracts_derivaitives	0.06966
FR3_contracts_derivatives	0.02212
FR1_contracts_portfolio	0.00993
FR2_contracts_portfolio	0.07453
FR3_contracts_portfolio	0.07204
FR1_contracts_balancesheet	0.07417
FR2_contracts_balancesheet	0.07250
FR3_contracts_balancesheet	0.03371
FR1_contracts_qifs	0.07218
FR2_contracts_qifs	0.09402
FR3_contracts_qifs	0.03525
FR1_contracts_collateral	0.05831
FR2_contracts_collateral	0.03109
FR3_contracts_collateral	0.03723