Government Borrowing and Crowding Out

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We investigate the impact of fiscal expansions on firm investment by exploiting firms with multiple banking relationships. Further, we conduct a localized approach and compare the lending behavior of banks that barely met and missed the criteria of being a primary dealer, as well as barely winners and losers at government auctions. Our results indicate that a 1 percentage point increase in primary dealer banks' bonds-to-assets ratio decreases loans by 0.2%, which leads to declines in firm investment, profits, and wages. Our findings are grounded in a quantitative model with which we compute the cost of borrowing on the economy.
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One of the lessons learned from the financial world crisis of 2008-2009 is that in the context of low, zero-bounded, or even negative interest rates, the effects of monetary policy are rather limited. With a decade slow of fragile recovery and the recent crisis brought forth by the Great Lockdown of 2020-2021, the effectiveness of fiscal policy is now at the forefront of macroeconomic debates. However, fiscal expansions (much more politicized than monetary policy according to Alesina and Giavazzi, 2013) are sometimes seen through an overly optimistic lens. In essence, advocates argue that they stimulate economic activity, scaled up by potential multipliers. The bulk of the supporting evidence today has its roots in the seminal papers of Mundell (1963) and Fleming (1962). In turn, critics highlight the dampening effects of lower investment. However, few empirical studies use micro data to support how resources to the private sector can be deterred by the take-up of government bonds (i.e., a crowding-out effect on lending).

In this paper, we investigate the impact of government spending on firm investment through the effect of cross-bank liquidity variation on corporate lending.

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To do so, we focus on the Colombian case, and specifically on firms that have multiple banking relationships. Namely, we trace firms' loan history across lenders as lenders absorb different levels of government debt. Similar to Mian and Khwaja (2008), we center on two main operating mechanisms: (i) the bank-lending channel which responds to bank-specific liquidity shocks, and (ii) the firm-borrowing channel which deals with firms' ability (or inability) to smooth out their debt across different sources of financing. This approach allows us to bridge the micro bank-lending literature with the macro crowding-out channel that evaluates banks' lending capacity when absorbing domestic public debt (Cook and Yetman, 2012, Ilzetzki, Mendoza and Vegh, 2013, and Bruno and Shin, 2015). More generally, our paper is closest to the empirical literature that exploits banks' heterogeneity to study the effects of macro shocks on firms' outcomes (Chodorow-Reich, 2014, Morelli, Perez and Ottonello, 2019, and Siriwardane, 2019).

We recognize that events that trigger changes in the liquidity supply, such as the take-up of government debt, are seldom exogenous and are often linked with changes in investment returns and credit demand. To overcome this endogeneity problem, our estimation strategy consists of two parts. First, we use the entire credit registry to evaluate the effects of banks' bond holdings on loans. Specifically, we report Panel OLS exercises with firm-time fixed effects allowing us to control for changes in the demand for credit. To control for supply factors, we include bank fixed effects as well as bank-level balance sheet information. Further, we examine the degree of loan substitution, i.e. whether firms are able to meet their loan demand by seeking credit from other banks once they fail to find resources from banks that take up government securities.

Second, we focus particularly on the primary dealer market, where primary dealers (*market makers*) benefit from having a special access to debt issuance from the government. In return, they are required by regulation to take on an established amount of government debt (i.e. to underwrite at least 4% - 5% of total debt issuance) and to participate actively in electronic trading platforms. Hence, our identifying assumption is based on the fact that a part of bond purchases in this market are exogenous (i.e. the amount that would have not otherwise been acquired). These purchases are not readily adjusted in banks' portfolio decisions and are more likely to be passed on as liquidity shortages to firms, dampening their credit lines.

To thin on our identification strategy, we conduct two types of Regression Discontinuity Design (RDD) exercises. In the first exercise we compare the lending behavior of banks that barely met the criteria of being a primary dealer with those that barely missed the cutoff. Intuitively, we expect the lending behavior of banks in the vicinity of the cutoff to be very similar ex ante. Thus, any change in private lending can be attributed to government debt issuance. In the second exercise we compare only across primary dealers: barely winners and losers at each auction. In this exercise we use, as running variable, the difference between each bid and the resulting cutoff price. Since neighboring bids reveal a similar valuation of government bonds, we exploit the fact that some bids receive a discontinuous treatment (i.e. winning the auction) and thus have fewer resources to lend out than those in the control group (i.e. auction losers).

Our study's main empirical contribution is hence to postulate a crowding-out effect as a function of public debt. That is, we confirm a crowding-out channel to corporates and find that this effect is more pronounced during episodes of high government debt. We stress the importance of primary dealers' take-up of sovereign bonds and in this sense, some papers close to our investigation are Broner et al. (2021), and Williams (2018), who find that, as the share of foreign-held public debt increases (i.e. fewer debt holdings by the banking sector), available credit to firms also increases. Our study also relates to Jiménez et al. (2014) in that we pay close attention to the triple interaction term between banks' holdings of government bonds, primary dealer banks, and total public debt.

Our study, to the best of our knowledge, is the first to establish a causal link (using micro data) wherein resources to the private sector are deterred by the take-up of government debt, leading to lower investment. Our findings indicate that a 1 percentage point (pp) increase in primary dealer banks' bonds-to-assets ratio decreases loans by 0.2% (we find a cumulative decline on loans of close to 1% over 12 months). We also find that the affected firms are only partially able to substitute their loans with other lenders. Our RDD results corroborate these findings: (i) primary dealers reduce their credit to corporates by 10.8% compared to non-primary dealers, and (ii) barely winners at government auctions reduce their credit lines by 19.3% compared to barely auction losers. A back-of-the-envelope calculation, based on the difference in bond holdings between primary and non-primary dealer banks, suggests a similar decline in loans of 1% in response to a government debt increase of a 1pp of GDP.

Additionally, we find some heterogeneous lending effects across firms. In particular, we show that the crowding-out effect is differentially lower for older and larger firms, for firms with more workers, and for firms with higher profits. Hence, these firms can cope better when faced with a sudden decrease in their credit lines. This is in line with some of the related literature, such as Holmstrom and Tirole (1997) who show that capital tightening affects poorly capitalized firms the hardest. Also, Chodorow-Reich (2014) shows that lender health affects employment but only at small and medium firms. Finally, Perez (2015) shows that an abundant (scarcer) supply of public debt makes banks shift towards (substitute away from) government securities and substitute away from (shift towards) investments in their less productive projects. Overall, this analysis is relevant because if banks are cutting more on low-productivity firms, this would reduce the misallocation in the economy. On the other hand, it warrants public policies targeted to the most vulnerable firms.

To shed some light on real sector effects, we compute a yearly firm-based measure of credit exposure: the share of primary dealer creditors of each firm over its total number of creditors. With this measure, and bearing in mind a weaker identification at this stage, we evaluate the effects on firm's outcomes. As a result, we find that credit exposure (scaled to a government debt increase of a 1pp of GDP) leads to a decline in liabilities, investment, profits, wages, and employment of 0.22%, 1.4%, 0.29%, 0.81%, and 0.16%, respectively.

On the quantitative side, we propose a closed-economy dynamic stochastic general equilibrium (DSGE) model with primary dealer banks, in order to rationalize the crowding-out effects of unanticipated government borrowing.[1] More generally, our model is part of the recent literature that investigates the effects of large sovereign bond holdings by banks. In particular, it is closely related to studies of credit-crunches (e.g., Gertler and Karadi, 2011, Kirchner and van Wijnbergen, 2016 and Bocola, 2016). Similar to Gertler and Karadi (2011) and Kirchner and van Wijnbergen (2016), our study is also closely related to the financial accelerator model developed in Bernanke, Gertler and Gilchrist (1999) which explores how constraints on the balance sheet can afflict the non-financial firm's ability of finding funds for their investment. However, different from Kirchner and van Wijnbergen (2016) and Bocola (2016), in our model banks face an exogenous increase in government's debt holdings, motivated by our empirical identification which also relies on exogenous bond purchases in the primary dealer market.

As key ingredients, financial intermediaries hold two types of assets: non-financial firm equity and government bonds. Also, government bonds are decomposed into endogenous and exogenous borrowing. The main mechanism for financial crowding out is as follows: an increase in exogenous government borrowing leads to a decrease in bank loans because the incentive compatibility constraint prevents the possibility of expanding the size of banks' balance sheets, and therefore induces a reduction in the other assets (endogenous public debt holdings and loans to firms). Further, higher public debt issuance also raises interest rates which reduces demand for corporate loans (used to produce capital goods) which in turn lowers investment, and through a contractionary effect in banks' balance sheets (i.e. financial accelerator mechanism), there is a sharp credit crunch in the economy. This chain of events also feeds into the entire economy by lowering wages and discouraging labor supply, all of which leads to a decline in household consumption.

Mapping the model with the empirical section is not straightforward. Unavoidably, pitfalls arise when matching the baseline empirical estimates (which we interpret as partial equilibrium effects on loans, i.e. leaving equilibrium prices and rates of returns fixed) with a general equilibrium model. To this end we first identify the partial equilibrium elasticity between changes in the exogenous government debt holdings and changes in loans, and then discipline this parameter with our empirical estimates. Then, we use the remaining general

[1]Colombia's access to foreign lending was negligible up until the 2014Q1 which justifies our closed economy assumption. A useful study that allows the government to have access to foreign lending in an open economy setting is Mimir and Sunel (2019) which extends Galí and Monacelli (2005).

equilibrium structure of the model to estimate the aggregate general-equilibrium crowding-out effect. Finally, we shed some light on issues that cannot be addressed in the empirical section, such as the unanticipated borrowing costs on various macroeconomic variables and conduct a welfare analysis.

Our paper proceeds as follows. In Section I we provide a detailed view of our case study, describe the data, and provide intuition for our main identification strategy. In Section II we present the empirical methodology and report our findings. In Sections III and IV we present our quantitative model, present calibrations, and report our results. Finally, Section V concludes.

I. The Colombian Case

A. Matching Firm and Bank-level data

In our empirical exercises, we use highly granular data, comprising the entire Colombian credit registry (at the loan level) from 2004 to 2015. This database, from the Financial Superintendency (*Superintendencia Financiera de Colombia, Formato 341*), contains over 5.5 million observations, with information on all loans extended to corporates, such as interest rate, loan amount, maturity, issuance date, expiration date, delinquency rate, and ex-ante credit rating. We merge these data with yearly firm-level balance sheet information from the Corporate Superintendency (*Superintendencia de Sociedades*) to include firm-specific variables such as asset size, liabilities, profits, wages, investment, and equity. In addition, we obtain data on employment from the Colombian Department of Labor, although only for the second half of the sample, as per data availability. After merging these sources, we match 1.5 million observations, which include a total of 30 private banks and 32,000 firms.

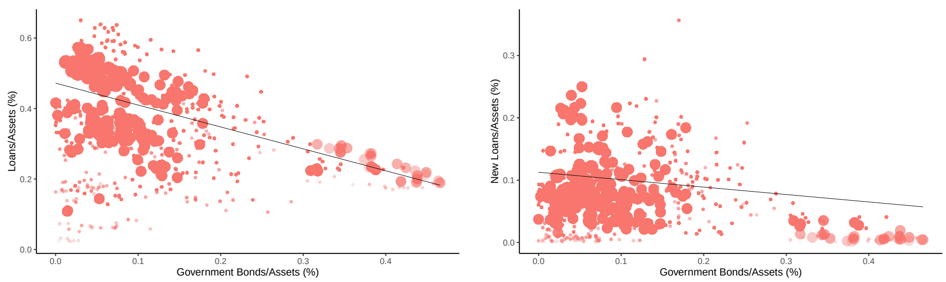
Given that our unit of measurement consists of new loans disbursed from bank j to firm i, we observe 730,000 new loans. Also, as a fundamental part of the study, we use private banks' total bond holdings of sovereign debt (*Títulos de deuda pública — TES*).

To give some initial context, an average Colombian bank has 3,400 new loans with different firms per month. However, large banks, with assets in the top 75th percentile of the banking system, account for 44% of the bank-corporate relationship. Additionally, a large bank has, on average, $2.4 trillion COP (0.24% of GDP) in government bonds, whereas the banking average reports an amount of $1.78 trillion COP.

B. Contextual characteristics

Figure 1 shows a seemingly negative relationship between banks' take-up of government bonds and their loan portfolio. Panel (a) shows the stock of loans along its y-axis and panel (b) shows the amount of new loans; both displayed as a share of total assets. Note that this is the main relationship that we evaluate in our investigation (in Section II, we claim causal evidence of government bonds on corporate loans). Notably, the figure displays some bank size heterogeneity in the take-up of government bonds.

We also shed light on the incremental effect brought forth by the country's total debt, that is, the overall impact that fiscal debt can exert on the crowding-out channel. Figure 2 shows that, during our sample period, the government debt (as a share of GDP) oscillated between 30% and 50%. This approach allows us to observe various debt levels with sufficient variation. Periods of high government debt took place at the onset of the millennium and after the year 2013.



(a) Stock of All Loans/Assets

(b) Flow of New Loans/Assets

Figure 1. : Stock and Flow of Loans

Note: Sovereign securities (x-axis) vs loans (y-axis). Each observation denotes one bank in a given month. The panels show the seemingly negative relationship between banks' government bonds holdings-to-assets ratio and loans-to-asset ratio (i.e. loans to corporates). The left panel shows the stock of loans in its y-axis while the right panel displays the amount of new loans, both as a share of total assets. The circle sizes are weighted according to bank size (value of bank's assets).

Table 1 provides descriptive statistics for the banking sector variables employed in our panel exercises, broken down by: (i) primary and non-primary dealers, and (ii) winner and loser banks at government auctions. We also include our loan-level dependent variable: the monthly volume of new loans, although aggregated at the bank level for readability purposes. The running variables used in the RDD exercises of Section 3.2, correspond to: (columns 1-4) the annual rankings of financial institutions, i.e. the criteria used to determine primary dealers, and (columns 5-8) the difference between each primary dealer's bid and the resulting cutoff price at government auctions. As observed, differences between banks diminish when in close proximity ($\pm$20%) of each threshold that determines the treatment status: primary and non-primary dealers (first treatment), as well as barely winners and losers at auctions (second treatment).

In turn, Table 2 shows descriptive statistics of our yearly firm-level variables. Note that in most of our empirical exercises, we use firm-time and bank fixed effects. Hence, several variables individually wash out of the regressions. Notwithstanding, when evaluating the effects on the real sector, we use firm-level data

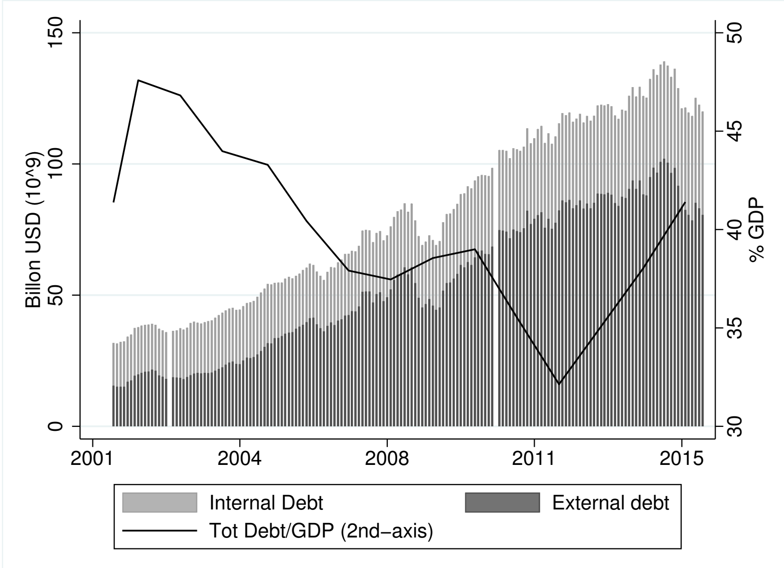


Figure 2. : Evolution of the Colombian government debt

Note: Internal debt (in COP) and external debt (mostly in USD), both in USD billions, are shown in the left y-axis, while total debt (as a share of GDP) is shown in the right y-axis.

(assets, investment, wages, employment, profits, liabilities, equity, age and risk) as dependent variables.

C. *Identification*

For expositional purposes, we refer to a crowding-out effect when government expenditure fails to boost aggregate demand due to a similar fall in private sector spending and investment (displayed as the movement from point B to point A in Figure 3). Intuitively, when the private sector lends money to the government, the resources available for private investment funding fall. However, if the economy is below its full capacity (point C), the increased spending does not necessarily lead to a crowding-out effect.[2]

A key challenge for identification is that the banking sector optimally balances its portfolio mix between government securities and corporate lending. In such an environment, our identification relies on firms' borrowing from multiple banks, one of which is a primary dealer bank. These primary dealer banks have privileged access to participate in government bond auctions. That is, apart from gaining a close relationship to the Ministry of Finance, they trade directly with

[2]As an example, Woodford (1990) argues that higher public debt can actually increase investment, by "reducing the extent to which people with access to productive investment opportunities are liquidity constrained" (page 386).

the government at prices dictated by weekly uniform clearing-price auctions in which they participate. Auction winners are also allowed to participate in non-competitive auctions, similar to a *greenshoe* option, at lower prices than secondary markets. Thus, a dealer has the potential to make significant gains if bond prices increase in the interim.

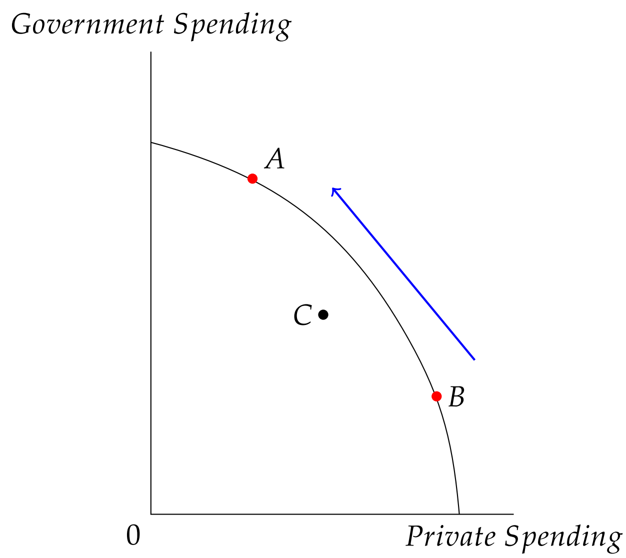


Figure 3. : The production possibilities curve

In return, they are required (by regulation) to take on a predetermined amount of government debt (i.e., to underwrite at least 4% - 5% of total government debt issuance). This restriction is largely binding: meeting the required amount in 87% of cases, and losing their primary dealer status in the remaining 13% of cases. Our identification strategy exploits this feature. We test whether primary dealers are more adversely affected during government spending booms.

A potential concern is that primary dealers off-load their government securities in a secondary market, to reduce their risk exposure. However, off-loading can be costly in terms of both time and price uncertainty (e.g., bond prices can change between the time banks purchase bonds at an auction and the time they sell bonds in a close-to-centralized secondary market). Further, primary dealers must show at least a 4.5% intake of total debt to avoid being penalized by the Financial Regulatory Authority (*Superintendencia Financiera de Colombia*).

Figures 4 and 5 investigate whether primary dealers are in fact off-loading securities. In the Colombian case, government auctions (primary market) are issued on two different days of the week, almost every week. Figure 4 depicts the net purchases of bonds (negative values for sales) by primary and non-primary dealer banks, each day relative to the auction day, at $t = 0$. Hence, period 1 is the day after each auction and period -1 is the day before (the figure stacks all auctions together). In essence, the figure shows that (i) primary dealers acquired more bonds during auction dates (attributable to auctions), and (ii) bond trading before and after the auction was similar for both primary and non-primary dealers. Visually, it does not appear that primary dealer banks purchased government bonds at auctions only to dispose of them in the secondary market.

Similarly, Figure 5 (left panel for total bonds and right panel for bonds/assets) displays the evolution of primary and non-primary dealers' share of government debt. It shows that primary dealers hold higher government debt and that the purchase amount difference relative to non-primary dealer banks is relatively constant through time. A potential concern is whether banks pledge these government securities to borrow from the Central Bank's discount window to increase lending to corporates (i.e. thorough repurchasing agreements -REPOs). However, this does not seem to be the case because the discount window facility is meant to help banks manage their short-term liquidity shortages, usually overnight, while corporate lending is conducted at longer-term maturities.

We recognize that primary dealers may differ systematically from the rest of the banking system. After all, Table 1 shows larger balances for primary dealer banks. This difference can be potentially unsettling if the reasons why they differ are also correlated with a stronger or weaker portfolio rebalancing after acquiring government debt. To rule out this concern, in Section II.C we conduct a localized approach using a regression discontinuity design (RDD), where we compare the behavior of banks that barely met the criteria to be primary dealers, with those that barely missed the cutoff. Finally, we note that primary dealers are designated annually, adding an additional source of exogeneity to our exercises.

II. Empirical Exercises and Results

In the empirical exercises that follow, we use loan level data containing information on 32,000 firms, 30 private banks, and 730,000 new loans from 2004 to 2015. Similar to Mian and Khwaja (2008), we restrict our attention to firms with multiple banking relationships to trace the entire loan history across lenders, as they change their stock of bond holdings. This approach allows us to observe different levels of government securities across banks (our treatment variable) for each firm. Our dependent variable focuses on new loans (credit flows) as opposed to credit stocks, since it allows for a clearer identification by filtering out pre-existing loans that would not be expected to react.

We recognize that events that trigger changes in banks' liquidity, such as the take-up of government debt, are seldom exogenous. In fact, one of the main empirical challenges to overcome is that of reverse-causality, where banks first reduce their exposure to private loans and then decide to buy government debt to substitute these loans. For example, demand factors such as lower investment opportunities for firms can lead to a decline in banks' lending. Additionally,

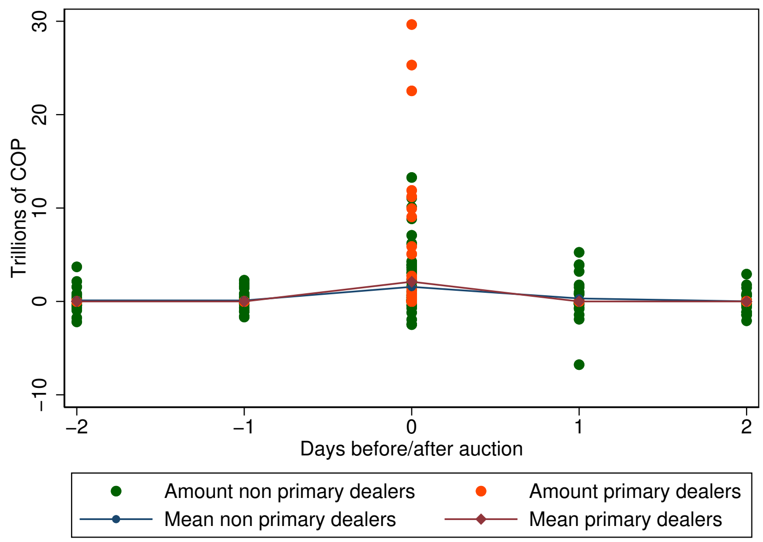


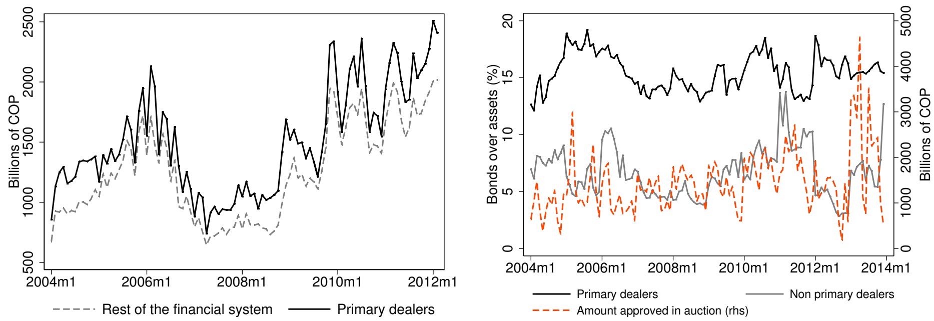
Figure 4. : Bond purchases by primary and non-primary dealers

Note: The figure plots the net daily amount of government bonds purchased by primary dealers and by the rest of the financial system. The diamonds represent averages.

supply factors associated with banks' portfolio risk can shift credit funds towards safer assets.

To overcome this endogeneity problem, our estimation strategy consists of two parts. First, in Section II.A we cover the entire financial system and compare each firm's loan relationship with its creditor vis-à-vis its other active creditors. We use firm-time fixed effects which overcome the demand-driven endogeneity concern that banks may acquire public debt if their firms are having bad investment opportunities. To control for supply factors, we include bank-level covariates, such as: excess reserves, provisions, total assets, equity, non-performing loans, and profits (see Table 1). We also use bank fixed effects and cluster standard errors at the bank level. However, while this exercise mitigates (to some extent) the concerns of reverse-causality, we acknowledge that there could still be unobservable factors, especially from the supply side, that could affect liquidity decisions for holding government bonds.

Hence, in order to thin on our identification strategy, in Section II.C we narrow in on the primary dealer market and employ a localized RDD approach. Specifically, we compare the lending behavior of: (i) banks that barely met the criteria of being a primary dealer with those that barely missed the cutoff, and (ii) auction winners and losers, in this second case restricting our focus to only primary dealers. We show that this localized approach, within the vicinity of the triggering threshold, allows for bond holdings to become uncoupled from both



(a) Amount in COP (b) Share Bonds/Assets

Figure 5. : Evolution of government debt holders

Note: The figure displays the monthly evolution of primary dealers' and non-primary dealers' amount of government debt (panel a) and as a share of banks' assets (panel b) over time. The dotted orange-red line in panel (b) presents the amount of government auctions along the right axis.

demand and supply factors.

Given the richness of the data, in Section II.E we explore whether the crowding-out effects are heterogeneous across firms. Namely, we study whether banks differentially reduce loans with firms that have different profitability, age, risk profile, employment, and size. We investigate this by introducing an interactive term both in the baseline regressions and in the ones that exploit the regression discontinuity.

Finally, in Section II.F we map our analysis to the real economy. That is, to shed some light on real sector effects, we propose a firm-based measure of credit exposure, capturing the extent to which lenders acquired government bonds and are thus more likely to be liquidity constrained. Using time-industry fixed effects we then evaluate the impact on firm's outcomes such as: wages, employment, investment, assets, liabilities, equity, and profits.

A. *Dampening of corporate credit lines*

We begin by evaluating the effects of banks' sovereign bond holdings on corporate loans by using the entire banking credit registry. Formally, we estimate the following regression model at the loan level and with a monthly frequency:

$$Loan_{i,j,t+h} = \alpha^h_{j,it} + \theta^h Bonds_{j,t-1} + \gamma^h Primary_{j,t-1} + \varphi^h ColDebt_{t-1} + \rho^h (Bonds * Primary)_{j,t-1} +$$

$$\eta^h (Primary * ColDebt)_{j,t-1} + \delta^h (Bonds * ColDebt)_{j,t-1} + \nu^h (Bonds * Primary * ColDebt)_{j,t-1} + \epsilon_{i,j,t+h} \quad (1)$$

where $Loan_{i,j,t}$ corresponds to the value (in logs) of all new loans from bank j to firm i, in month t. The variable $Bonds_j$ denotes the bank's stock of government bonds as a share of its assets. $Primary_j$ indicates the amount of bonds purchased in the primary dealer market by bank j, also as a share of its assets (non-primary dealer banks take a zero value). The term $\alpha_{j,it}$ indicates bank and firm-time fixed effects. Finally, $ColDebt_t$ is the macroeconomic variable denoting total government debt over GDP, which individually washes out of the regressions because of the time fixed effects. In the spirit of Jordá's (2005) method of local projections, we estimate sequential regressions in which loans are shifted forward each month. Specifically, we estimate equation (1) for $h = 0 - 11$ which correspond to the effects on months 1-12.

It remains to show whether firms are able to meet their loan demand by seeking credit from other banks i.e., once they fail to find resources from a primary dealer bank. This issue is related to the work of Chodorow-Reich (2014), which verifies the importance of banking relationships and the implied cost to borrowers who switch lenders. In essence, it sheds light on general equilibrium effects of government spending on the banking sector's entire lending capacity. More generally, this determination provides some intuition on whether the economy is lying at point C of Figure 3, i.e. if firms' financing can be sourced from non-primary dealer banks at no cost, then this would suggest that the economy is operating below capacity. Hence, we explore whether firms that borrow from primary dealer banks can substitute their loans from non-primary dealer banks. As such, we estimate a similar version of equation (1) but now using as dependent variable other loans of firm i (excluding loans with bank j), as follows:

$$Loan_{i,\text{-}\mathbf{j},t+h} = \tilde{\alpha}^h_{j,it} + \tilde{\theta}^h Bonds_{j,t-1} + \tilde{\gamma}^h Primary_{j,t-1} + \tilde{\varphi}^h ColDebt_{t-1} + \tilde{\rho}^h (Bonds * Primary)_{j,t-1} +$$
$$\tilde{\eta}^h (Primary * ColDebt)_{j,t-1} + \tilde{\delta}^h (Bonds * ColDebt)_{j,t-1} + \tilde{\nu}^h (Bonds * Primary * ColDebt)_{j,t-1} + \tilde{\varepsilon}_{i,j,t+h} \quad (2)$$

where the marginal effect of $Bonds_j$ and $Primary_j$ now evaluate the degree of loan substitution: an increase in primary dealer bank j's bond holdings, which decreases its credit line with firm i, forces the firm to look for additional credit. Hence, if the amount of loans deterred (equation 1) is greater (in absolute value) than the amount of new loans acquired with other creditors (equation 2), then the firm is only partially able to substitute its loans.

B. Results: dampening of corporate credit lines

In Figures 6-8 we report the implied Impulse Response Functions (IRFs) of equations 1 and 2. Notice that the response (changes in loans) is denoted in percentages (%) and the impulse is in terms of a 1 percentage point (pp) increase in the share of bonds-to-assets.[3]

In the left panels (panels a) we report the partial derivative of loans with respect to the amount of bonds purchased by primary dealers: $\partial^2 Loan_{i,j} / \partial Bonds_j \partial Primary = \rho + \nu(ColDebt)$, and in the right panels (panels b) we report the partial derivative of loans with respect to the amount of bonds purchased by primary dealers de-

[3]The magnitude of the impulse is useful since, on average (across banks and time), a 1pp increase in the bonds-to-assets ratio represents a bond increase in the amount of 112 billion (10^9) COP. This amount is similar to a government debt increase of 1% of GDP (6.5 trillion COP), since roughly 25% is acquired by the banking sector (0.25*6.5=1.625) and when distributed among the 15 banks at a given point in time yields 1.625/15= 108 billion COP per bank.

pending on the level of Colombian debt: $\partial^3 Loan_{i,j}/\partial Bonds_j \partial Primary_j \partial ColDebt = \nu$.[4] For robustness, and also to conceptually set the stage for the RDD exercises of the next section, we also report estimates when restricting the sample to four institutions per year: two barely accepted primary dealers and two institutions that barely missed the cutoff to become primary dealers. Note that this is equivalent to running a Weighted Least Squares (WLS) regression giving equal weight to banks close to the cutoff and zero elsewhere.

Results of equation (1) are shown in Figure 6. As shown in panel (a), the negative effect of primary dealer banks' bond holdings on loans is significant from month 6-9. Specifically, in period 8 (peak month) we find a reduction in loans of 0.2%. In total, we find a cumulative decline in loans of 1.08% over 12 months. Similarly, our WLS specification shows loan reductions in 0.2% and significant through period 10. As shown in panel (b), primary banks and bond holdings have a negative incremental effect when the government issues more debt, i.e. in period 8, a 1pp increase in the triple interaction term decreases loans by 0.5%.

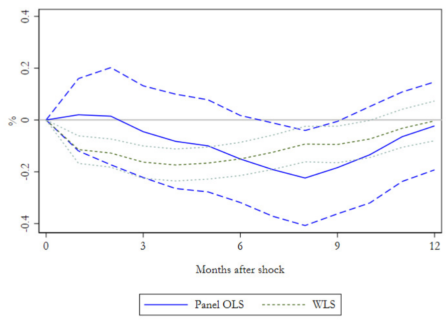
In turn, credit availability with other lenders (see equation 2) has a positive but smaller (substitution) effect. The IRF of Figure 7 shows that a 1pp increase in a lender's bonds-to-assets ratio leads the firm to acquire credit with other lenders by 0.15% (in period 8). The incremental effect of $Bonds * Primary * ColDebt$ is also smaller, showing an increase in loans with other lenders by up to 0.31%. To statistically assess the overall effect, in Figure 8 we consider all loans of firm j $(Loan_{i,j} + Loan_{i,-j})$ as dependent variable. We confirm that firms are only partially able to substitute out their debt: firms reduce their total credit in up to 0.06% (period 8).

C. *Localized RDD approach*

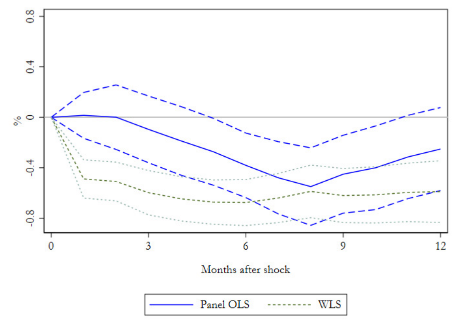
In this section we conduct two types of regression discontinuity design (RDD) exercises: (i) one that compares the lending behavior of banks that barely met the criteria of being a primary dealer with those that barely missed the cutoff, and (ii) one that compares across primary dealers: barely winners and losers at each auction. Regarding the former, every year the Ministry of Finance publishes the rankings of financial sector participants that compete every year to be part of the "market makers" program for public debt securities. Given limited membership, only the institutions ranked 10^{th} or above become primary dealers. Regarding the latter, government auctions operate under a weekly uniform clearing price structure, where the government sells bonds to all winners at the same cutoff price.[5]

[4]For expositional purposes we evaluate Colombian debt in the top decile to illustrate when the economy operates at its full capacity (see Section I.C).

[5]Given that there are multiple auctions during the auction date (conducted weekly) and that each bank can register multiple bids per auction, we compute (for each winner) an average weekly bid, weighted by



(a) Interaction *Bonds* ∗ *Primary*



(b) Interaction *Bonds* ∗ *Primary* ∗ *ColDebt*

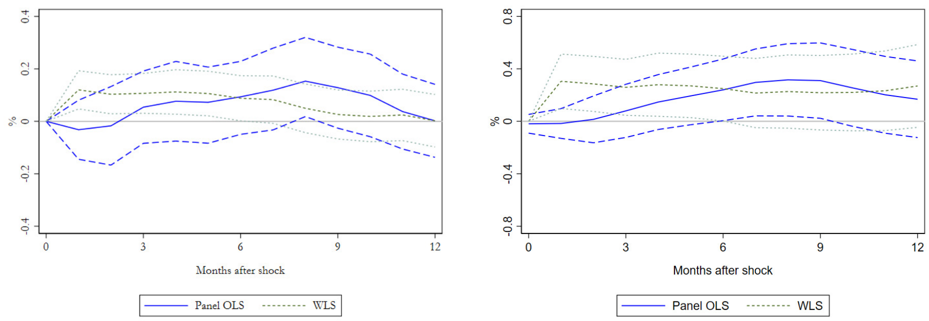
Figure 6. : IRFs of banks' bond holdings on corporate loans (in %)

Note: The sample includes all months from December 2004 to December 2015. Each listed coefficient results from equation (1). The dependent variable, $Loan_{i,j,t+h}$, corresponds to the value (in logs) of all new loans from bank j to firm i, in month $t+h$. *Bonds* denotes the bank's stock of government bonds as a share of its assets. *Primary* indicates the amount of bonds purchased in the primary dealer market, also as a share of its assets. The WLS regression is restricted to a bandwidth of 2 (relative to the ranking of primary dealers). Confidence bands denote statistical significance at the 5% level. For all regressions, the average R^2 is 0.80 with 60,000 observations.

Our main identifying assumption is that *locally*, there are no significant differences between these banks (apart from being a primary dealer or winning at an auction) that correlate with their demand for loans and public debt. While this assumption cannot be fully tested, it does have some testable implications. In particular, in Table 3 we present a falsification test in which we regress the treatment status (a dummy variable indicating whether the bank is a primary dealer or if it won at a government auction) on banks' balance sheet information. As observed, treatment is partially explained by variables such as liquidity, excess reserves, profits, and provisions. However, when restricting the sample to a smaller bandwidth (within the vicinity of the triggering threshold), treatment becomes uncoupled from these factors. In fact, columns 4 and 8 show that only the condition that triggers the rule –the running variable– is significant. This suggests that the lending strategy of banks within the vicinity of each cutoff point is similar ex ante.

Further, we note that primary dealers are designated every year and that the same bank wins and loses auctions at different points in time, adding an additional source of exogeneity to our exercises. This can be seen in Figure 9 where we plot the different financial entities (x-axis) according to their running variable (y-axis). More specifically, panel (a) shows the banks' annual rankings,

the volume purchased. Similarly, for each auction loser (i.e. losing in all auctions during the auction day) we compute its average bid, weighted by volume offered. Auction regulations (2822 of 2002, 3766 of 2009, and 3781 of 2009) are provided by the Ministry of Finance and can be accessed in the Financial Superintendency's website: https://www.superfinanciera.gov.co/jsp/16127.



(a) Interaction $Bonds * Primary$ (b) Interaction $Bonds * Primary * ColDebt$

Figure 7. : IRFs of banks' loans substitution (in %)

Note: IRFs of banks' loans substitution (in %). The sample includes all months from December 2004 to December 2015. Each listed coefficient results from equation (2). The dependent variable, $Loan_{i,\text{-j},t+h}$, corresponds to the value (in logs) of all new loans to firm i but excluding loans from bank j, in month $t+h$. *Bonds* denotes the bank's stock of government bonds as a share of its assets. *Primary* indicates the amount of bonds purchased in the primary dealer market, also as a share of its assets. The WLS regression is restricted to a bandwidth of 2 (relative to the ranking of primary dealers). Confidence bands denote statistical significance at the 5% level. For all regressions, the average R^2 is 0.80 with 60,000 observations.

i.e. the criteria used to determine the status of being a primary dealer (non-negative if primary dealer), and panel (b) shows the difference between each primary dealer's bid and the resulting cutoff price at weekly government auctions (non-negative if winner).

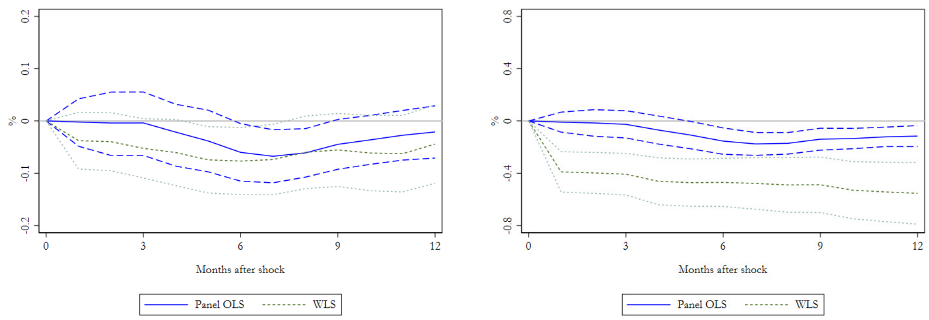
We next proceed to evaluate the impact of treatment on lending. Formally, the bank's assignment of treatment $(\hat{D}_{j,t})$ is deterministically determined by the running variable $(X_{j,t})$, as follows:

$$\hat{D}_{j,t} = \mathbf{1}\left\{X_{j,t} \geq r\right\} \tag{3}$$

where $\mathbf{1}$ denotes an indicator function and r denotes the treatment threshold. We then estimate a similar specification as that of equation (1), only now set locally around either the bank's eligibility criteria to become a primary dealer or the auction's clearing price:

$$\arg\min_{\theta} \sum_{ij=1}^{I\times J}\sum_{t=0}^{T}\left[Loan_{i,j,t+1} - \alpha - \theta\hat{D}_{j,t} - b\left(X_{j,t}-r\right) - \tau\hat{D}_{j,t}\left(X_{j,t}-r\right)\right]^2 K\left(\frac{X_{j,t}-r}{k}\right) \tag{4}$$

where θ accounts for the average treatment effect, i.e. the effect of loans due to being a primary dealer. Note that the running variable $(X_{j,t})$ corresponds to either the annual rankings of financial sector participants or to the difference between each bid and cutoff price at weekly government auctions. Also, $Loan_{i,j,t}$ is the amount of new loans (aggregated either annually or weekly) up until before the next ranking or auction takes place. Finally, $K(\cdot)$ is a triangular kernel



(a) Interaction $Bonds * Primary$ (b) Interaction $Bonds * Primary * ColDebt$

Figure 8. : IRFs of banks' bond holdings on corporate loans (in %)

Note: IRFs of banks' bond holdings on corporate loans (in %). The sample includes all months from December 2004 to December 2015. Each listed coefficient results from equation (1). The dependent variable, $Loan_{i,j,t+h} + Loan_{i,\mathbf{-j},t+h}$, corresponds to the value (in logs) of all new loans from bank j to firm i plus all new loans from other banks $-j$ to firm i, in month $t+h$. $Bonds$ denotes the bank's stock of government bonds as a share of its assets. $Primary$ indicates the amount of bonds purchased in the primary dealer market, also as a share of its assets. The WLS regression is restricted to a bandwidth of 2 (relative to the ranking of primary dealers). Confidence bands denote statistical significance at the 5% level. For all regressions, the average R^2 is 0.80 with 60,000 observations.

with bandwidth k and the inclusion of the term $\hat{D}_{j,t}\left(X_{j,t} - r\right)$ allows for different specifications of how the running variable affects the outcome, at either side of the cutoff point. We consider optimal bandwidth choices as described in Imbens and Kalyanaraman (2012) and also report bandwidth sizes twice as optimal (2x).

D. RDD Results

Results are reported in Table 4 and show that loan values pertaining to primary dealers and auction winners are lower than for non-primary dealers and auction losers. Specifically, primary dealers reduce their credit to corporates by 10.8%, and auction winners (among primary dealers) by 19.3%.

To obtain a better sense of the magnitude of these results, we report that banks that barely missed being a primary dealer have 1.4 trillion COP in government bond holdings whereas banks that barely got accepted as primary dealers have 2.6 trillion COP (see Table 5). The difference between them (1.2 trillion COP) is nearly 11-fold the amount reported in Section II.B in terms of new bonds per bank after a government debt increase of 1pp of GDP. Hence, a back-of-the-envelope calculation suggests that loans decrease in roughly 1% (10.8/11) in response to a government debt increase of 1pp of GDP.

Additionally, similar to the exercises in Section II.A, we explore whether these effects are further magnified when we include the interaction term of bonds-to-assets ratio. Specifically, we find that a 1pp increase in banks' bonds-to-assets

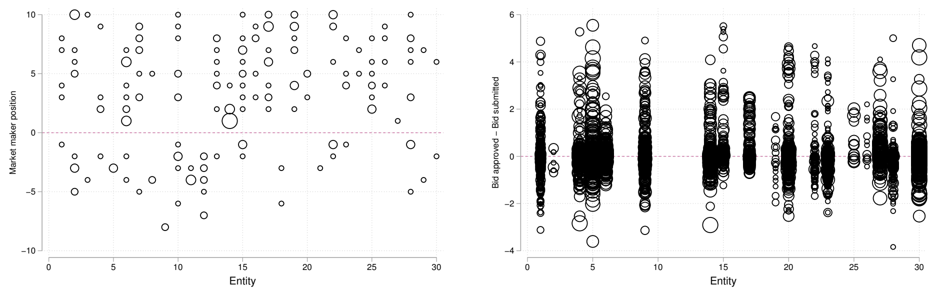


Figure 9. : Assignment of treatment

Note: Panel (a) shows the ranking (position) of each financial entity (x-axis), where non-negative values denote a primary dealer status. Panel (b) shows the difference between a dealer's bid and the auction cutoff price, where non-negative values denote winning the auction. The size of each bubble represents the frequency in which the entity obtained a specific value of the running variable. For anonymity purposes, the ordering of entities in panel (a) is not necessarily the same as in panel (b).

ratio has a negative incremental effect on loans of 0.02% and 0.84% for primary dealers and auction winners, respectively. Intuitively, the set of primary dealers and auction winners reduce their credit lines to corporates vis-à-vis non primary dealers and auction losers, but even more so when the former have larger government bond holdings.

For robustness, the lower pane of Table 4 shows a placebo test that evaluates the effect of the same treatment status, but on lagged outcomes (lagged loans). As expected, results show a null effect of treatment on past outcomes.

E. Firm Heterogeneity

We next investigate whether the crowding-out effects are heterogeneous across firms. To do so, we interact firm-level variables such as profitability, age, risk profile, employment, and size, with creditors' bond holdings. Similar to the exercises presented in Section II.A, in Table 6 we present results for new corporate loans, using the entire banking credit registry.

Results reported in columns 2, 3, 5 and 6 show that the crowding-out effect is differentially lower (less negative) for older and larger firms, firms with more workers, and firms with higher profits. To exemplify, in period 7, a 1pp increase in banks' bonds-to-assets ratio decreases loans to firms by 0.41% on average, but in lesser magnitude for the largest firms. Alternatively, the crowding-out effect increases as a function of firms' ex ante loan risk (i.e. lower loan grade provided by the creditor).

In Table 7 we present RDD results, which are analogous to those in Section II.C. Given the yearly frequency of the firm-level variables, we only report results for banks that barely met or missed the criteria of being a primary dealer.[6] Similar to the previous exercise, primary dealers reduce their credit to corporates by 10.8% but in lesser magnitude for variables such as age, employment, size, and profits. We also find an increased crowding-out effect for firms with a high ex ante loan risk.

These results are in line with some of the related literature. In particular, Holmstrom and Tirole (1997) show that capital tightening affects poorly capitalized firms the hardest. Also, Chodorow-Reich (2014) shows that lender health affects employment but only at small and medium firms. Finally, Perez (2015) shows that an abundant (scarcer) supply of public debt makes banks shift towards (substitute away from) government securities and substitute away from (shift towards) investments in their less productive projects.

Overall, this analysis is relevant because if banks are cutting more on low-productivity firms, this would reduce the misallocation in the economy. On the other hand, it warrants public policies targeted to the most vulnerable firms.

F. Effects on the real sector

To shed light on the impact of the overall crowding-out channel on the real sector, we first compute a firm-level *credit exposure* variable that captures the extent to which their lenders acquired government bonds. Specifically, we measure the firm's number of creditors that qualify as primary dealers over its total number of creditors, as follows:

$$Credit\_Exposure_{i,t} = \frac{1}{J}\sum_{j}\mathbf{1}\left\{Primary\_Bank_{i,j,t}\right\} \tag{5}$$

where $\mathbf{1}\left\{Primary\_Bank_{i,j}\right\}$ is an indicator function turned on for primary dealers banks. Intuitively, high values of credit exposure implies that the firm is borrowing from liquidity constrained banks. With this measure, and bearing in mind a weaker identification at this stage, we evaluate the effects on firm's outcomes using yearly corporate balances from the Corporate Superintendency (*Superintendencia de Sociedades*). Formally, we estimate the following model:

$$y_{i,t} = \alpha_{ts} + \beta Credit\_Exposure_{i,t-1} + \epsilon_{i,t}, \tag{6}$$

where the term α_{ts} accounts for time-industry fixed effects, and $y_{i,t}$ includes variables such as assets, liabilities, investment, profits, and wages.

Results are presented in Table 8 and confirm the negative real sector effects when resources to the private sector are deterred by the take-up of government bonds. Specifically, in the specification that controls for time-industry fixed effects,

[6]Recall that the exercise on barley winning and losing an auction is conducted at a weekly frequency, so the firms' yearly variables would remain unchanged at every auction during a given year.

a 1pp increase in the measure of credit exposure leads to a decline in liabilities, investments, profits, wages, and employment of 0.032%, 0.213%, 0.043%, 0.12%, and 0.024%, respectively. Note that effects last for one year before subsiding (except for liabilities, whose effects last for two years).

Similar to Section II.D, we report that the average non-primary dealer bank has 1.1 trillion COP in government bond holdings whereas the average primary dealer bank has 2.7 trillion (see Table 5). And, since the exposure variable (for each firm) covers the range of all banks being non-primary dealers (exposure=0) to all banks being primary dealers (exposure=1), then a 1pp increase in credit exposure represents, under a linear setting, a bond increase of 16 billion COP (2.7-1.1)/100. Also, recall from Section II.B that a government debt increase of 1% of GDP, when distributed among the banking sector, yields approximately 108 billion COP per bank. Hence, a back-of-the-envelope calculation suggests that results can be scaled nearly seven-fold (108/16) for an impulse interpretation of a government debt increase of 1% of GDP, leading to a decline in liabilities, investments, profits, wages, and employment of 0.22%, 1.4%, 0.29%, 0.81%, and 0.16%, respectively.

III. A Quantitative Model of Crowd-out of Public Debt

To rationalize our empirical findings, in this section we propose a crowding-out model of public debt. To map our empirical results to the quantitative section, we make some simplifications. For instance, we only consider primary dealer banks in a closed economy setting. Thus, the banking sector has a fixed lending capacity. That is, an increase in government spending reduces the available credit to firms as agents in the economy cannot borrow from abroad.

In the model that follows, an increase in exogenous government borrowing leads to a decrease in loans because the incentive compatibility constraint prevents the possibility of expanding the size of banks' balance sheets, and therefore induces a reduction in the other assets (endogenous public debt holdings and loans to firms). Also, when the government increases its borrowing unexpectedly, interest rates on government securities increase, and banks pass on these costs to firms, which induces a further decline in demand for capital and crowds-out investment of capital producer firms. We then show how this mechanism propagates to the entire economy through lower wages and discouraged labor supply.

Lastly, we bring our empirical estimates closer to data by first identifying the partial equilibrium elasticity between changes in the exogenous government debt holdings and changes in loans, and then discipline this parameter with our empirical estimates. Then, we use the remaining general equilibrium structure of the model to estimate the aggregate general equilibrium crowding-out effect. Additionally, we use our quantitative model to provide economic insights that cannot be addressed in the empirical section, such as the unanticipated borrowing costs on various other macroeconomic variables and conduct a welfare analysis.

A. Model Description

Our setup comes from the class of models with sticky prices and financial intermediation that builds on Christiano, Eichenbaum and Evans (2005), Smets and Wouters (2007), Gertler and Karadi (2011), Kirchner and van Wijnbergen (2016), among others. We extend the basic structure to enable the role of primary dealer banks in meeting the government's deficit financing needs. The model has two sectors: a private sector (households, firms, and financial institution) and a public sector (a monetary authority that determines the risk-free nominal interest rate according to a Taylor rule and a government that purchases final goods from firms and conducts financial sector policies). The financing of the government is met through borrowing from primary dealer banks.

This section describes the key equations as well as the new assumptions required for the financial institution, mainly primary dealers, which play a key role in our framework. The rest of the model segments are by now standard.[7] Thus, all detailed descriptions and derivations are relegated to the online appendix.

B. Financial institution: primary dealer banks

Following Gertler and Karadi (2011) and Kirchner and van Wijnbergen (2016), banks are subject to informational frictions. The key ingredient in our setup is the arrangement of an exogenous increase in public debt balances on top of optimal debt issuance. The reason why we model the government borrowing this way is motivated by our identification strategy in the empirical model. Recall that our identifying assumption in Section II.A is based on the fact that a part of bond purchases in the primary dealer market are exogenous (i.e. the amount that would have not otherwise been acquired). This enables us to investigate how an unanticipated increase in the government's financing needs affects the economy and can bring the quantitative analysis closer to our empirical analysis.

Turning to the relevant section of the model, banks are competitive and total assets of an intermediary j at the end of period t reads:

$$a_{j,t} = q_t s_{j,t} + b^g_{j,t} + b^{prim}_{j,t}, \tag{7}$$

with $s_{j,t}$ denoting bank j's claims on intermediate good firms that have a relative price of q_t and a net real return of r^k_{t+1} at the beginning of next period. The bank holds two assets, $b^g_{j,t}$ and $b^{prim}_{j,t}$ where each asset pays a net real return of r^g_{t+1} and

[7] To summarize the production chain, there are four agents taking part, all of which are owned by households. Perfectly competitive intermediate good producing firms rent labor services from households and borrow from banks by issuing claims to finance capital acquisition. At the end of the production of intermediate good firms, capital producers purchase their capital, repair their depreciated capital, purchase investment goods, and transform them into new capital. This new capital is again purchased back by intermediate goods producers who sell their differentiated goods to monopolistically competitive retail firms which re-package these goods and sell it to the final goods producers whose job is to transform these varieties into a single good.

r_{t+1}^{prim} in the next period. Note that the bank cannot choose how much $b_{j,t}^{prim}$ to hold in its debt balances as $b_{j,t}^{prim}$ are government bond holdings that the bank is required to hold because of its primary dealer status. The balance sheet of bank j is then given by:

$$a_{j,t} = d_{j,t} + n_{j,t},$$

where $d_{j,t}$ denote household deposits made to the bank j and the last term $n_{j,t}$ denotes the bank j's net worth which can be dynamically written as the difference between asset earnings and liabilities that bear interest:

$$\begin{aligned} n_{j,t+1} &= (1+r_{t+1}^k)q_t s_{j,t} + (1+r_{t+1}^g)b_{j,t}^g + (1+r_{t+1}^{prim})b_{j,t}^{prim} - (1+r_{t+1}^d)d_{j,t} \\ &= (r_{t+1}^a - r_{t+1}^d)(a_{j,t} - b_{j,t}^{prim}) + (r_{t+1}^{prim} - r_{t+1}^d)b_{j,t}^{prim} + (1+r_{t+1}^d)n_{j,t}, \end{aligned} \tag{8}$$

where r_{t+1}^a is the net ex-post real portfolio return excluding $b_{j,t}^{prim}$ debt holdings because of the intermediary's primary debt holding status. Note that, while all returns on government bonds are endogenously determined, the interest rate spread between the exogenous and endogenous components of public debt ($r^g - r^{prim} > 0$) reflects the cost of being a primary dealer and is empirically motivated by the fact that primary dealers bear this unanticipated shock (see Section II.A).[8] With portfolio weights $\omega_{j,t} = q_t s_{j,t}^k/(a_{j,t} - b_{j,t}^{prim})$ and $1 - \omega_{j,t} = b_{j,t}^g/(a_{j,t} - b_{j,t}^{prim})$, r_t^a satisfies:

$$1 + r_t^a = (1+r_t^k)\omega_{j,t-1} + (1+r_t^g)(1-\omega_{j,t-1}). \tag{9}$$

Equation (8) illustrates that banker j's net worth depends positively on the premia of the returns earned on assets over the cost of deposits. It also shows that with a positive return difference between bankers' portfolio and deposits, net worth may explode and bankers may self-finance over time. As in the literature, particularly after Gertler and Karadi (2011), at any point in time a constant proportion of household members become bankers and the remaining ones become workers (an individual can switch between the two over time). The literature assumes a constant survival probability of a banker to rule out a possibility of complete self-financing. In particular, a banker operates with probability θ and exits with probability $1-\theta$, during which retained capital is transferred to the household. The banker's objective is to maximize the expected value of discounted terminal

[8]Details of this interest rate spread are provided in the calibration section. The underlying assumption is that banks would have lent to firms otherwise. Nonetheless, we also repeat the analysis by assuming that both exogenous and endogenous components of public debt holdings have the same rate of return and results are provided in the online appendix. We show that results remain qualitatively highly similar.

net worth of $V_{j,t}$ as follows

$$V_{j,t} = \max_{s^k_{j,t+1+i}, b^g_{j,t+1+i}} E_t \sum_{i=0}^{\infty} (1-\theta)\theta^i \beta^{i+1} \Lambda_{t,t+1+i} n_{j,t+1+i},$$

which can be written recursively as,

$$V_{j,t} = \max_{s^k_{j,t+1}, b^g_{j,t+1}} \beta E_t \Big\{ \Lambda_{t,t+1} \left[(1-\theta) n_{j,t+1} + \theta V_{j,t+1} \right] \Big\}. \tag{10}$$

With positive return rates, the solution to this maximization problem may generate indefinite expansion of assets. We rule out this by following Gertler and Karadi (2011) where they introduce an agency problem between depositors and financial intermediaries. In particular, depositors believe that bankers can divert a constant fraction λ^* of total current assets, $a_{j,t}$. When depositors become aware of such a confiscation scheme, they would initiate a bank-run and liquidate the bank's net worth. To rule out a bank run in equilibrium, an incentive compatibility constraint $V_{j,t} \geq \lambda^* a_{j,t}$ must be satisfied. This inequality suggests that the cost to the banker of diverting assets should be greater or equal to the diverted portion of assets. So the maximization problem becomes:

$$\max_{s^k_{j,t}, b^g_{j,t}} V_{j,t} \quad \text{s.t.} \quad V_{j,t} \geq \lambda^* a_{j,t}.$$

The solution to this problem closely follows Gertler and Karadi (2011) and Kirchner and van Wijnbergen (2016) and again is relegated to the appendix.

C. *Government borrowing*

The government purchases final goods and undertakes borrowing with one-period bonds to finance its operations. Following Kirchner and van Wijnbergen (2016), let b_{t-1} denote the government's outstanding debt holdings at the beginning of a period. Taxes follow the following rule

$$\tau_t = \overline{\tau} + \kappa_b (b_{t-1} - b), \tag{11}$$

with $\kappa_b \geq 0$ and $\overline{\tau} > 0$. This tax rule ensures fiscal solvency for any finite initial level of debt (Bohn (1998)). As noted before, the government's borrowing decision has two ingredients, b^g and b^{prim}, of which the first part can be anticipated by banks, but b^{prim} comes as a surprise.

The stock of total government debt that are held by banks satisfies the following law of motion:

$$b_t = g_t - \tau_t + (1 + r_t^g)b_{t-1}^g + (1 + r_t^{prim})b_{t-1}^{prim}. \tag{12}$$

Government purchases of b^{prim} follows the exogenous process:

$$log(b_{t+1}^{prim}) = (1 - \rho^{prim})log(\overline{b^{prim}}) + \rho^{prim}log(b_t^{prim}) + \varepsilon_{t+1}^{prim}, \tag{13}$$

where ε_{t+1}^{prim} is a Gaussian process with zero mean and constant variance. Total government debt thus follows $b_t = b_t^g + b_t^{prim}$.

D. *Aggregation, market clearing and equilibrium*

All households and banks behave symmetrically and they all face the same asset prices. Thus, we can aggregate our equations over j, derive market clearing conditions, and define equilibrium sequences that satisfy these conditions along with a number of first-order and transversality conditions obtained from the optimization problem of agents. For readability purposes, the details are relegated to the online appendix.

IV. Model analysis

We now use our model to analyze the costs of an unexpected increase in government borrowing. We first present the calibration and show that the model can match business cycle statistics of our case study (Colombia). We then link our model variables with our empirical results (as tight as possible) to investigate the costs of an unexpected increase in government borrowing.

A. *Calibration*

The calibration has two main ingredients: (i) one resorting to the data and (ii) one relying on conventional estimates that are commonly used in New Keynesian DSGE models. The list of parameters used in the paper is provided in Table 9. Our (quarterly) data cover the sample period from 2000Q1 to 2020Q1.

In particular, we follow the parametrization found in Gertler and Karadi (2011) for the degree of habit formation υ, the inverse Frisch elasticity of labor supply φ, the elasticity of substitution among intermediate goods ϵ, the probability of keeping prices fixed ψ, share of effective capital α, investment adjustment cost parameter γ and the depreciation rate of capital δ. The parameters of the Taylor rule are set to conventional values of 1.5 for the feedback coefficient on inflation κ_π, 0.125 for the output gap coefficient κ_y and 0.8 for the interest rate smoothing parameter ρ_r. To match the annualized deposit rate of 7%, we set β to 0.983.

To match Colombia's macroeconomic data, the steady state ratio of government spending over GDP (g/y) is set to 18.3% and the ratio (b/y) is set to 1.8 which implies an annual government-debt-to-GDP ratio of 45%. Primary dealer banks' share of total government debt holdings is set to 25%. This value often ranges between 15%-45% in the data, but on average it is equal to 25%. We also present our results when this value is set to ⅙ or ⅓. The quarterly depreciation rate of capital (δ) is set to 4.5% to match the average investment-to-capital ratio.

The next block of parameters concern the financial sector. Gertler and Karadi (2011) discuss the difficulties in calibrating the steady state leverage ratio, as there is a high degree of heterogeneity in the financial and non-financial sector's leverage ratio. Even in the financial sector, the leverage ratio varies among commercial and investment banks. We discipline the choice of this parameter by targeting the partial equilibrium elasticity between changes in the exogenous government debt holdings and changes in loans. We estimate this elasticity value to be 1% and set ϕ to be 4 (see Section II). The survival probability of bankers (parameter θ) is mainly used to ensure that newly entrant bankers, details of which are provided in the online appendix, receive a positive amount, χ. By setting it to 0.95, which implies that the average survival duration of bankers is 5 years, we obtain proportional transfer to the entering bankers to be 0.009 which is also similar to the value obtained in Gertler and Karadi (2011). Note that our calibration implies that the fraction of assets that can be diverted (λ) becomes = 0.195. Finally, the steady state credit spread (Γ) is set to 330 annual basis points to match the spreads of bank lending rates to T-bills.

B. Model versus Macro Data

The quantitative performance of the model economy calibrated to Colombian data is illustrated in Table 10, in which the volatilities, correlations with output, and autocorrelations of the simulated time series are compared with corresponding data moments. To match key empirical business cycle moments, we have turned on the shocks to TFP, government expenditures, and the monetary policy rate. In particular, the parameters of the productivity shock (ρ_z, σ_z), the government spending shock (ρ_g, σ_g) and the standard deviation of the i.i.d. shock to the monetary policy rule (σ_i) are selected to match the standard deviations of the cyclical components of Colombia's real GDP (Y), consumption (C), private investment (I), government expenditures (G) and the policy rate for the period 2000Q1–2020Q1.[9]

[9]Real GDP, real private consumption and investment series are obtained from Colombia's National Administrative Department of Statistics (DANE) https://www.dane.gov.co/. Public debt, CPI, policy rate and domestic gross total loans are obtained from the Central Bank of Colombia https://www.banrep.gov.co/. The remaining ones are obtained using Bloomberg except Moody's Seasoned Aaa Corporate Bond Yield, which is used to compute the credit spreads, available on the St. Louis Fed's database http://research.stlouisfed.org/fred. All variables, except the policy rate and spreads, are log transformed and demeaned. The model moments are computed from 10,000 simulated time series. Cyclical components of the model and the data are estimated using a Hodrick-Prescott (HP) filter with a smoothing parameter of 1600.

The first, third and fifth columns of Table 10 show the point estimates of empirical moments (standard deviations, first-order autocorrelations and cross-correlations with respect to GDP) along with associated standard errors in parentheses. It appears that consumption is less volatile than output, whereas government expenditure, private investment, and government borrowing are significantly more volatile than output. Concerning financial variables, except inflation, all the other variables (policy rate, credit spread, bank credit, bank capital) are more volatile than output. The remaining columns in the table display the simulated moments obtained using the Delta method and GMM. We report the t-statistics in brackets to assess the statistical difference between the model implied moments and the data moments. Even though the benchmark model is not estimated and includes a few number of shocks, the model does a relatively good job in matching the relative volatilities of model variables of interest, as the t-statistics lie below 2 in absolute value for real GDP, consumption, investment, government expenditures, government debt, policy rate, and credit spread.

Concerning the autocorrelations, the model performs well too. Column 4 displays that the model matches the autocorrelations observed in the data, except for private investment and inflation, which have associated t-statistics below 2 in absolute value. Column 6 shows that the correlations with output, the level of model-implied correlation coefficients, besides the policy rate, which follows from the negative correlation between inflation and output and credit spread, are fairly similar to those implied by the data. Most importantly consumption, investment, government spending, and bank credit are procyclical in the data and the model. Our conclusion from this analysis is that the model performs reasonably well for a fair description of the basic properties of the business cycle statistics.

C. *Comparing the model with the empirical section*

We now assess whether the quantitative model connects to the empirical estimates. As a word of caution, comparing our empirical strategies and quantitative model is not straightforward. Unavoidably, pitfalls arise as we try to match micro-estimates with a general equilibrium macro model. To name a few, our empirical strategy first identifies the impact of government borrowing on corporate lending and for that we use several control variables, fixed effects (e.g. we use firm-time fixed effects to control for credit demand), or employ a localized approach. In the quantitative model, however, instead of controlling for demand, we model it (some effects are in fact driven by firm's credit demand).[10] Further, in all of our empirical regressions, we investigate the impact of a 1 percentage point (pp) increase in primary dealer bank's bonds-to-asset ratio, which roughly coincides with a 1pp of GDP increase in government bonds. In contrast, in the quantitative

[10]In our main analysis in Section II.B, the cumulative fall in the amount of net capital is 1.08% after an unanticipated 1% increase in government borrowing.

model we measure the impulse of the borrowing shock as a 1pp of GDP relative to the steady state.

To account for this discrepancy we interpret the baseline empirical estimates as the partial equilibrium effects on loans (leaving fixed equilibrium prices and rates of returns). Intuitively, in the empirical analysis, we are essentially estimating the incremental effect of increasing the exogenous component of bond holdings for primary dealers relative to non-dealers.[11] Thus, we compute the partial equilibrium responses of loans to changes in b^{prim}, details of which are provided in the online appendix and target this elasticity in the model to match the empirical estimates. Recall from our empirical analysis that the elasticity of increasing marginal costs of raising external finance is approximately 1%. Key parameters in measuring the elasticity of increasing marginal costs of raising external finance are ϕ and the share of exogenous government debt in bank's balances in the steady state. For that, we set ϕ to 4 and set the share of exogenous government debt to its long-run average which is ¼.

Next, we use the remaining general equilibrium structure of the model to estimate the aggregate general-equilibrium crowding-out effect. The results of this analysis are reported in the second column of Table 11. Recall from Section II.F, and also summarized in the first column of Table 11, that a government debt increase of 1% of GDP leads to a decline in investments, wages, and employment of 1.4%, 0.81%, and 0.16%, respectively. On the quantitative front, notice that the investment panel in Figure 10 displays a steady state deviation of investment of -0.11% at its peak but dies out quickly. As a result, the cumulative investment decline, computed for 1,000 periods, becomes 1.48% which is reported in the second column of Table 11. Similarly, the cumulative fall in wages and labor amounts to 0.33% and 0.15%.

Our conclusion from this analysis is that our quantitative model provides a fair description of the main empirical estimates. Further, in the next subsection we perform a welfare analysis which cannot be evaluated in our empirical strategy.

D. Effects of a surprise borrowing shock

We now investigate the response to a surprise borrowing shock. Our objective is to understand how the economy responds when the government's funding pressures are passed on to primary dealer banks when it borrows unanticipatedly. Figure 10 plots the impulse response functions of selected variables to an unanticipated increase in government borrowing. We consider three alternative shock levels. The baseline scenario is the one in which the b^{prim} shock is normalized to 1% of GDP on impact with an auto-correlation coefficient ρ_b of 0.95, with which we target to match the cumulative capital decline observed in our empirical sec-

[11]This policy can have aggregate effects, which would correspond to adjustments in the endogenous component and on loans through changes in the rate of returns. However, these are presumably what the estimation is abstracting from by using the non-primary dealers as controls.

tion as elaborated in the previous section. The other two shock levels considered are b^{prim} normalized to 0.5% and 2% of GDP.

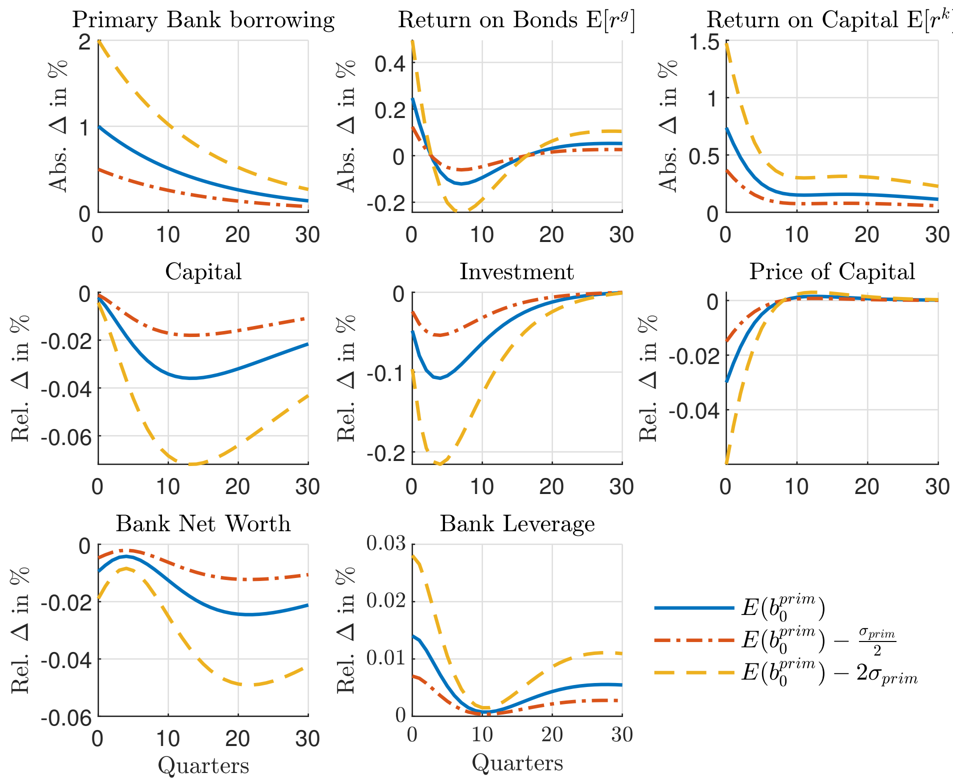


Figure 10. : Impulse-response functions

Note: Impulse-response functions of selected model variables to a surprise borrowing shock of 0.5%, 1% , 2% of GDP relative to steady state in quarter 0. The figures show deviations from the steady state.

The main mechanism at work is as follows. A rise in exogenous government borrowing b^{prim} leads to a crowding-out in bank loans because the incentive compatibility constraint prevents the possibility of expanding the size of banks' balance sheets, and therefore induces a reduction in the other assets (endogenous public debt holdings and loans to firms). Notice that in the baseline scenario, plotted in solid blue lines in the figure, the initial impact of a rise in borrowing is reflected in the sharp jump in both expected interest rates and borrowing costs. As the cost of borrowing increases, goods producers demand less capital which crowds out investment of capital producers. Notice that the fall in investment is amplified even though the shock is mean-reverting. This follows from the financial accelerator mechanism, as in Gertler and Karadi (2011). At the core of this mechanism lies the procyclical variation in the bank's balance sheet. In particular, a decline in investment leads to a reduction in the price of capital, which reduces the valuation of claims on intermediate goods firms, and thus leads to a further tightening in the bank's net worth. These adverse conditions tighten endogenous leverage constraints that banks must meet while providing loans to producers and the government. This chain of events raises borrowing costs, crowds out investment, lowers asset prices, contracts the bank's net worth, and so forth. As a result, there is a sharp credit crunch in the economy. Figure 11 shows that the entire economy is affected by this chain reaction as the effects feed through by lowering workers' wages and discouraging labor supply which tightens household's budget constraint and leads to a decline in consumption. The response of the economy depends on the size of the shock that is fed into the economy.

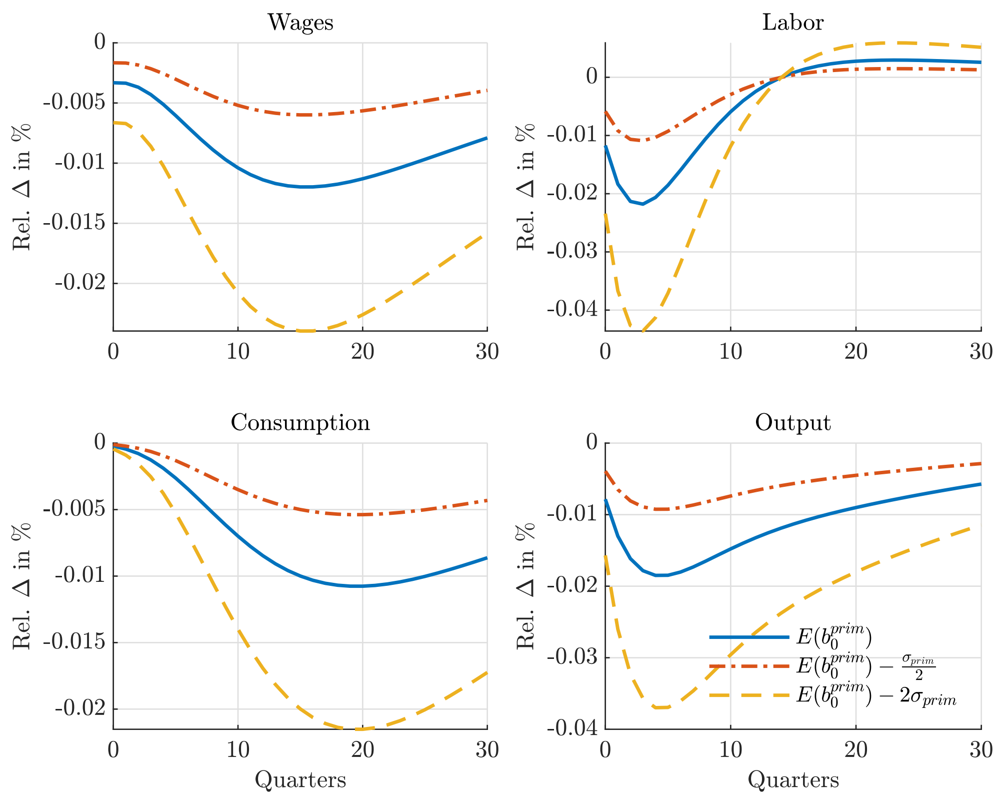


Figure 11. : Impulse-response functions

Note: Impulse-response functions of wages, labor, consumption and output to a surprise borrowing shock of 0.5%, 1% , 2% of GDP relative to steady state in quarter 0. The figures show deviations from the steady state.

To sharpen the understanding of the model dynamics, we proceed by changing the steady state value of the share of government debt passed on to primary dealer banks. Recall that the steady state share of primary dealer debt is around one-third of total government debt. We hence consider two values, ⅓ and ⅙, denoted as "high borrowing" and "low borrowing", respectively. The b^{prim} shock is normalized to 1% of GDP on impact and the outcome of this analysis is presented in Figures 12 and 13.

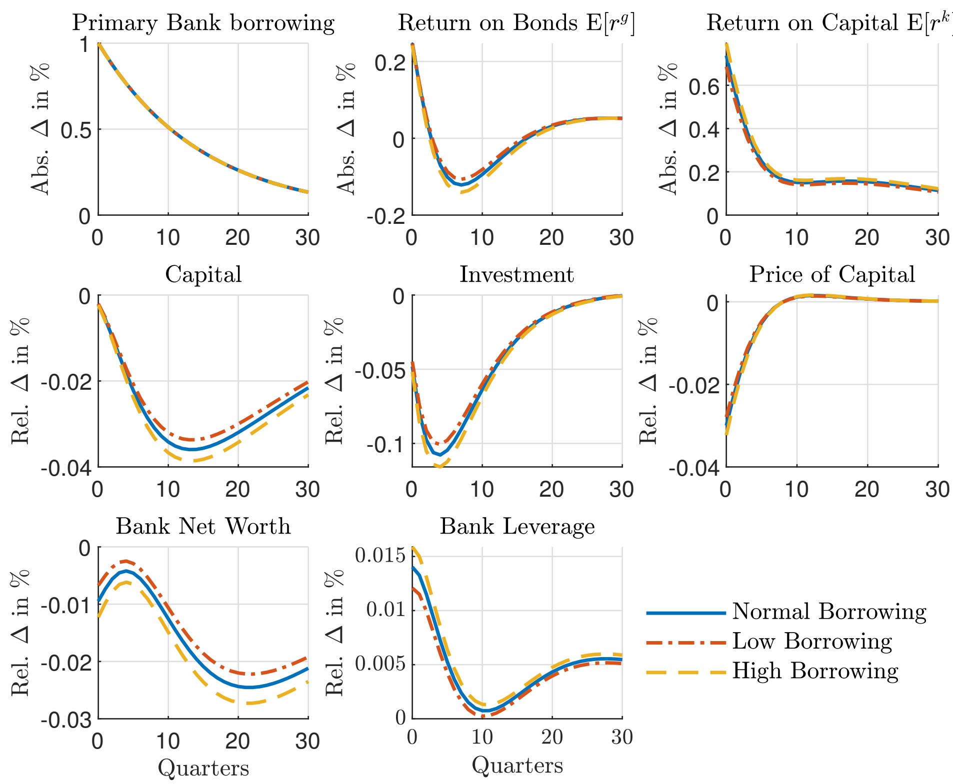


Figure 12. : Impulse-response functions

Note: Impulse-response functions of selected model variables to a surprise borrowing shock of 1% of GDP relative to steady state in quarter 0. The figures show deviations from the steady state.

In essence, a rise in the government's unanticipated borrowing generates similar paths for expected interest rates and borrowing costs. This is different from the analysis in Figures 10 and 11 in which we considered different levels of borrowing shocks. Nevertheless, the magnitude of the decline in capital and investment is smaller in the case with a lower borrowing shock. This is because the rise in government borrowing does not crowd out banks' claims to firms as much as for

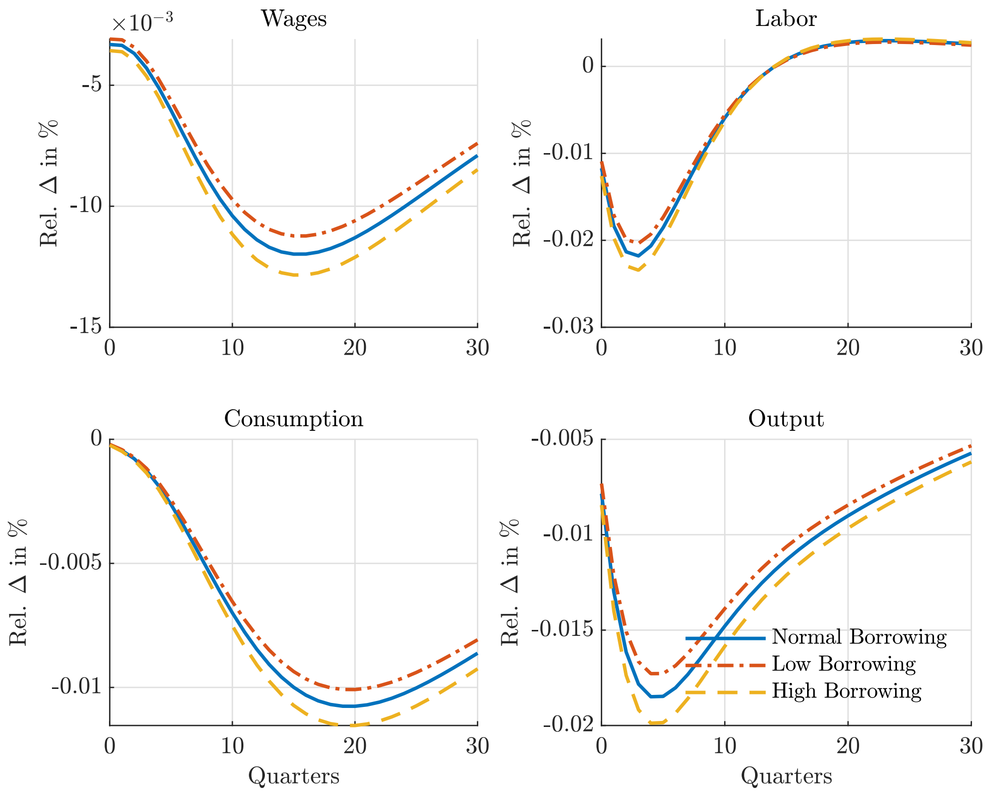


Figure 13. : Impulse-response functions

Note: Impulse-response functions of wages, labor, consumption and output to a surprise borrowing shock of 1% of GDP relative to steady state in quarter 0. The figures show deviations from the steady state.

the case of higher borrowing. Thus, banks only need to channel fewer funds to government borrowing leading to a milder credit crunch in the economy.

E. Welfare analysis

We now use our model to evaluate the cost of government debt issuance in an economy where government debt crowds out bankers' demand for capital claims issued by non-financial firms leading to a decline in investment. To do so, we undertake a welfare analysis. The criterion used for this analysis is the unconditional steady state value of household's lifetime utility, provided in equation (A.1) in the online Appendix. We implement a second-order approximation to the utility function of the representative agent around the steady-state and then evaluate welfare under different degrees of the borrowing shock. In particular, we compute welfare gains in percentage changes in compensating consumption variations that would leave households indifferent between staying in an economy with an unanticipated increase in government borrowing or moving to an economy without an unanticipated increase. Thus, a negative value would imply that a household would prefer to live in an economy without a borrowing shock.

Figure 14 depicts the welfare gains from being in the economy with government borrowing shocks. As shown, welfare is always lower in the economy with borrowing shocks and the degree of the fall in welfare varies depending on the size of the shock. Specifically, the borrowing shock normalized to 1% of GDP on impact generates a welfare loss of 0.0015% at the onset and to 0.0022% at its peak. Notice that when the magnitude of the shock is doubled (halved), the severity on welfare amplifies (is reduced). As a result, the cumulative welfare loss, which corresponds to the discounted average computed for 1,000 periods, is 0.08%.

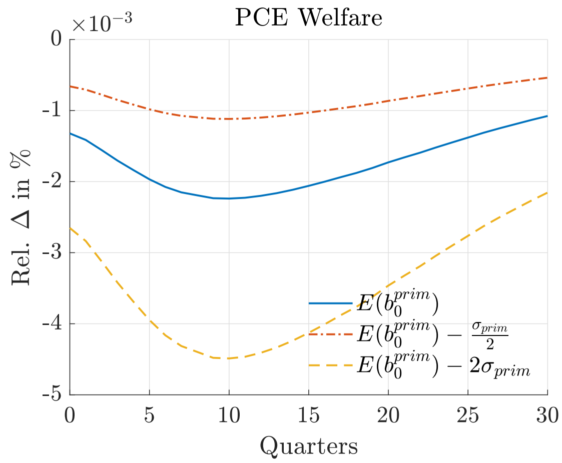


Figure 14. : Welfare gains

Note: The effects of a borrowing shock on welfare measured in permanent consumption equivalent (PCE) terms.

V. Conclusions

We investigate the potential dampening effect of government spending on firm investment by closely tracing firms with multiple banking relationships. On the empirical front, we postulate a crowding-out effect as a function of public debt. That is, we confirm a crowding-out channel to corporates and find that this effect is more pronounced during episodes of high government debt. At the core of our identification strategy lies the role of primary dealer banks, required, by regulation, to take on an established amount of government debt and actively participate in electronic trading platforms.

All of our results point toward how increased government borrowing affects the dynamics of economic activity and crowds out private investment. In particular, we find that an increase in banks' bonds-to-assets ratio decreases loans to corporates. Additionally, we show that the crowding-out effect is differentially lower for older and larger firms, firms with more workers, and firms with higher profits. Hence, these firms can cope better when faced with a sudden decrease in their credit lines. Finally, we find that firm's outcome variables are negatively exposed.

Our findings are grounded in a quantitative model with financial and real sectors. In contrast to most of the literature, our framework is enriched with investment, financial sectors and long-term debt. We show that increased government spending limits the amount of available funds to firms and raises sovereign risk. Primary dealers then pass on these costs to local firms.

Our study, to the best of our knowledge, is the first to establish a causal link (using micro data) wherein resources to the private sector are deterred by the take-up of government debt, which in turn leads to lower investment. Hence, our findings can better guide fiscal and monetary policymakers, especially during spending booms.

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Table 1—: Bank-level Descriptive Statistics (Sample Means)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Across all Banks				*Across Primary Dealers*			
	PD	**Non-PD**	**PD**	**Non-PD**	**Winner**	**Loser**	**Winner**	**Loser**
	Whole Sample		**Threshold ±20%**		**Whole Sample**		**Threshold ±20%**	
Dependent variable								
New loans[a]	1.691	1.129	2.402	0.850	1.443	1.537	1.140	1.576
	(10.196)	(4.596)	(7.336)	(0.592)	(5.100)	(4.792)	(3.706)	(3.572)
Running variable	4.928	-3.333	0.895	-1.688	0.594	-0.390	0.024	-0.024
	(2.912)	(1.706)	(0.875)	(0.479)	(0.972)	(0.574)	(0.015)	(0.014)
Covariates								
Liquidity	1.152	1.115	1.151	1.100	1.350	1.139	1.141	1.137
	(0.052)	(0.049)	(0.062)	(0.023)	(4.413)	(0.049)	(0.053)	(0.049)
Excess reserves	0.001	0.002	0.0007	0.0004	0.152	0.001	0.0008	0.0007
	(0.002)	(0.005)	(0.0023)	(0.0010)	(5.696)	(0.006)	(0.007)	(0.004)
Provisions[a]	0.645	0.092	0.260	0.005	0.198	0.308	0.420	0.449
	(2.883)	(0.356)	(0.570)	(0.013)	(1.669)	(1.888)	(2.870)	(3.478)
Total assets[b]	26.44	9.80	23.11	11.87	10.62	18.57	24.11	23.73
	(22.99)	(5.60)	(19.78)	(5.52)	(13.90)	(16.82)	(21.23)	(19.68)
Equity	0.130	0.102	0.129	0.091	0.131	0.120	0.122	0.119
	(0.038)	(0.036)	(0.047)	(0.018)	(0.087)	(0.037)	(0.040)	(0.037)
NPL	0.039	0.036	0.040	0.035	0.050	0.041	0.039	0.039
	(0.021)	(0.018)	(0.022)	(0.016)	(0.044)	(0.021)	(0.024)	(0.019)
Profits	0.0006	0.0007	0.0008	0.0002	0.0013	0.0004	0.0004	0.0004
	(0.0021)	(0.0018)	(0.0023)	(0.0003)	(0.018)	(0.002)	(0.0022)	(0.0023)

Authors' calculations. Standard deviations are reported in parenthesis. PD (Non-PD) denotes primary and non-primary dealers and Winner (Loser) denotes auction winners and losers. The running variables (used in the RDD exercises of Section 3.2) correspond to: (columns 1-4) the annual rankings of financial institutions, and (columns 5-8) the difference between each primary dealer's bid and the resulting cutoff price at government auctions. [a] Variables are in billion COP (10^9) and [b] are in trillion COP (10^{12}). Equity and profits are measured as a share of assets. Liquidity is defined as assets over liabilities, NPL is defined as overdue loan portfolio over gross loan portfolio, and excess reserves is measured as reserves over deposits.

Table 2—: Firm-level Descriptive Statistics

Dependent Variable	(1) **Mean**	(2) **Std. Dev.**	(3) **P25**	(4) **P50**	(5) **P75**
Assets	16.14	63.92	1.45	3.96	11.39
Investment	3.04	75.99	0.016	0.13	0.99
Wages	0.07	0.33	0.003	0.02	0.042
Liabilities	17.51	93.9	1.246	3.50	10.71
Profits	8.75	52.31	0.801	2.03	5.57
Equity	16.98	139.25	0.799	2.26	6.93
Age	17.67	11.49	8.77	15.43	24.94
Employment	83.75	605.34	4	11	36
Risk	4.95	0.28	5	5	5

Authors' calculations. Total assets, investment, wages, liabilities, profits, and equity are in billion COP (10^9). Firm investment includes shares, quotas, securities, corporate papers, and any other negotiable document acquired temporarily or on a permanent basis, with the purpose of maintaining a secondary liquidity reserve, establishing economic relations with other entities, or to meet legal or regulatory provisions. Age is the number of years of the firm. Employment is the number of firm employees (for this variable we have information for only the second half of the sample, as per data availability from the Department of Labor). Risk corresponds to the weighted average (by loan amount) of the credit rating.

Table 3—: RDD Falsification Test

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Primary Dealer (yearly)				Winner of Auction (weekly)			
Variables/bandwidth	All	BW = 4	BW = 3	BW = 2	All	BW = 0.3	BW = 0.2	BW = 0.05
Running Variable	0.080***	0.245***	0.339***	0.442***	0.363***	4.046***	5.727***	20.01***
	(0.004)	(0.023)	(0.046)	(0.127)	(0.014)	(0.040)	(0.060)	(0.329)
Liquidity	0.882*	0.387	0.103	0.087	-0.193	0.269*	0.300*	0.374
	(0.525)	(0.973)	(1.449)	(1.714)	(0.130)	(0.144)	(0.156)	(0.252)
Excess reserves	-4.504	-57.66**	5.825	252.3	1.091	1.081	1.106	2.429
	(4.026)	(24.62)	(54.36)	(572.2)	(1.251)	(0.962)	(1.091)	(3.421)
Profits	14.01	86.13***	19.38	-227.7	-2.189	-1.093	0.046	4.153
	(14.30)	(24.98)	(52.54)	(553.6)	(2.793)	(3.648)	(4.352)	(4.938)
Provisions	0.010	-0.018**	0.426*	0.272	0.005*	0.001	0.0004	-0.001
	(0.009)	(0.009)	(0.208)	(0.233)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	112	46	30	17	3,996	2,755	2,290	879
R-squared	0.724	0.699	0.760	0.631	0.270	0.593	0.613	0.616
F-test all	109.4	41.49	44.25	3.214	142.3	2019	1847	747.7
pvalue all	0	0	0	0.049	0	0	0	0

Each column reports a linear bank-level regression with the treatment dummy D_t (Primary Dealer or Winner of Auction). BW denotes the bandwidth size (relative to the ranking or bid). The running variables correspond to: (columns 1-4) the annual rankings of financial institutions, and (columns 5-8) the difference between each primary dealer's bid and the resulting cutoff price at government auctions. The sample covers 2004-2015. Excess reserves is measured as reserves/deposits and profits as a ratio of assets. Robust standard errors are in parentheses, and *, **, and *** represent statistical significance at the 10%, 5%, and 1% level, respectively. Constant is not reported.

Table 4—: Localized effect of being a Primary Dealer and winning an auction

	(1)	(2)	(3)	(4)
	Primary Dealer		Winner of Auction	
	$\hat{D}_{it}$	$Bonds * \hat{D}_{it}$	$\hat{D}_{it}$	$Bonds * \hat{D}_{it}$
Loans				
Optimal Bandwidth	-0.108***	-0.024***	-0.193***	-0.837***
	(0.019)	(0.002)	(0.010)	(0.058)
2x Optimal Bandwidth	-0.851***	-0.031***	-0.219***	-1.617***
	(0.031)	(0.002)	(0.007)	(0.043)
Placebo Test				
Lag Loans				
Optimal Bandwidth	-0.013	0.004	0.097	-1.078
	(0.063)	(0.010)	(0.083)	(1.578)
2x Optimal Bandwidth	0.010	0.004	0.083	-0.195
	(0.050)	(0.007)	(0.063)	(0.662)
Observations	54,139	53,170	185,716	181,466

Authors' calculations. The sample covers 2004-2015. The dependent variable is the value (in logs) of all new loans from bank j to firm i, in year t (columns 1-2) or in week t (columns 3-4). The running variables correspond to: (columns 1-2) the annual rankings of financial institutions, and (columns 3-4) the difference between each primary dealer's bid and the resulting cutoff price at government auctions. In the lower panel, the placebo dependent variables are the yearly lag of assets and the lag value of loans. The interaction term is between the primary dealer status (column 2) or winning the auction (column 4) and the bank's stock of government bonds as a share of its assets. Reported RDD estimates correspond to equation (4). Bandwidth choices (optimal and 2x optimal) are based on Imbens and Kalyanaraman (2012).

Table 5—: Assets and bond holdings between primary and non-primary dealers

	Primary Dealers			Non-Primary Dealers		
	All	BW = 2	BW = 3	All	BW = 2	BW = 3
Bonds	2,705	2,692	2,633	1,132	1,399	1,412
Assets	17,381	13,924	17,462	7,816	10,525	10,049
Bonds/Assets	0.13	0.24	0.20	0.11	0.20	0.18

Authors' calculations. BW denotes the bandwidth size (i.e. number of institutions that barely missed and passed the criteria for being primary dealers). Variables are in billion COP (10^9).

Table 6—: Incremental effect of banks' bond holdings on corporate credit (Panel)

	(1)	(2)	(3)	(4)	(5)	(6)
		Interaction effect with *Bonds*				
Periods	*Bonds*	*Age*	*Employment*	*Risk*	*Size*	*Profits*
1	-0.17	0.031***	0.025***	0.006	0.014**	0.016**
	(0.17)	(0.009)	(0.006)	(0.005)	(0.006)	(0.006)
2	-0.27	0.012	0.006	-0.002	0.013**	0.012
	(0.18)	(0.011)	(0.004)	(0.006)	(0.005)	(0.007)
3	-0.29*	0.029**	0.007	-0.005	0.015**	0.013**
	(0.16)	(0.011)	(0.008)	(0.004)	(0.005)	(0.005)
4	-0.34**	0.023**	0.010	0.001	0.015***	0.014***
	(0.14)	(0.011)	(0.008)	(0.006)	(0.004)	(0.005)
5	-0.31*	0.014	0.001	-0.004	0.009	0.007
	(0.16)	(0.009)	(0.005)	(0.010)	(0.005)	(0.005)
6	-0.41***	0.025*	0.019**	-0.008	0.011*	0.008
	(0.13)	(0.012)	(0.008)	(0.005)	(0.005)	(0.005)
7	-0.41***	0.018*	0.003	-0.002	0.015***	0.015**
	(0.14)	(0.009)	(0.006)	(0.006)	(0.004)	(0.005)
8	-0.29**	0.012	0.003	-0.006	0.013*	0.012**
	(0.14)	(0.009)	(0.006)	(0.007)	(0.006)	(0.005)
9	-0.37***	0.032***	0.005	-0.003	0.017***	0.013***
	(0.13)	(0.008)	(0.005)	(0.008)	(0.005)	(0.003)
10	-0.18	0.009	0.004	-0.010**	0.011**	0.008
	(0.19)	(0.010)	(0.005)	(0.004)	(0.004)	(0.005)
11	-0.12	0.024**	0.004	-0.007	0.011	0.011
	(0.16)	(0.010)	(0.009)	(0.005)	(0.007)	(0.007)
12	-0.13	0.039***	0.013**	-0.009	0.017**	0.018**
	(0.18)	(0.009)	(0.006)	(0.006)	(0.006)	(0.008)
Clustered by bank	yes	yes	yes	yes	yes	yes
Firm-time fixed effects	yes	yes	yes	yes	yes	yes
Bank fixed effects	yes	yes	yes	yes	yes	yes
Bank controls	yes	yes	yes	yes	yes	yes

Authors' calculations. The sample includes all months from December 2004 to December 2015. Each listed coefficient results from a separate regression following equation (2). Rows denote outcomes h-months after treatment. The dependent variable, $Loan_{i,j,t+h}$ corresponds to the value (in logs) of all new loans from bank j to firm i, in month $t+h$. *Bonds* denotes the bank's stock of government bonds as a share of its assets. Age, Employment, Size and Profits are categorical variables that take the value of 1 if values are less than the 25^{th} percentile, 2 if between the 25^{th} and 75^{th} percentile, and 3 if greater than the 75^{th} percentile. Risk is a dummy variable that takes the value of 1 if the ex ante loan grade is below perfect score. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. For all regressions, the average R^2 is 0.80 with 60,000 observations.

Table 7—: Incremental effect of being a Primary Dealer (RDD)

	(1)	(2)	(3)	(4)	(5)	(6)
		Interaction effect with *Bonds*				
	Bonds	*Age*	*Employment*	*Risk*	*Size*	*Profits*
Optimal Bandwidth	-0.108***	0.009***	0.106***	-0.278***	0.121***	0.0011*
	(0.019)	(0.0004)	(0.011)	(0.012)	(0.007)	(0.0006)

Authors' calculations. The sample covers 2004-2015. The dependent variable is the value (in logs) of all new loans from bank j to firm i, in year t. The running variable corresponds to the annual rankings of financial institutions. Columns (2-6) correspond to the interaction term between the primary dealer status ($\hat{D}_{it}$) and firm specific variables. Reported RDD estimates correspond to equation (4). Bandwidth choices are based on Imbens and Kalyanaraman (2012).

Table 8—: Impact of lenders' bond holdings on firms' balances

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Assets	Δ Liabilities	Δ Investments	Δ Profits	Δ Wages	Δ Employment
–Time FE and Industry FE–						
			t			
Credit_Exposure$_{i,t-1}$	-0.019	-0.032***	-0.260**	-0.045**	-0.118***	-0.022
	(0.013)	(0.011)	(0.121)	(0.020)	(0.040)	(0.015)
Obs	17,054	17,053	4,354	16,906	14,526	7,335
R^2	0.033	0.032	0.019	0.023	0.029	0.015
			t+1			
Credit_Exposure$_{i,t-1}$	-0.0003	-0.0385**	-0.0092	0.0305	0.0600	0.0002
	(0.0193)	(0.0160)	(0.163)	(0.0285)	(0.0526)	(0.0186)
Obs	17,055	17,054	4,359	16,906	14,527	7,337
R^2	0.033	0.031	0.018	0.021	0.028	0.012
			t+2			
Credit_Exposure$_{i,t-1}$	-0.0004	-0.0110	-0.0484	0.0144	0.0503	-0.0087
	(0.0264)	(0.0189)	(0.0925)	(0.0375)	(0.0864)	(0.0273)
Obs	17,054	17,053	4,348	16,906	14,525	7,333
R^2	0.015	0.017	0.019	0.014	0.014	0.013
–Time-Industry FE–						
			t			
Credit_Exposure$_{i,t-1}$	-0.018	-0.032***	-0.213*	-0.043**	-0.120***	-0.024*
	(0.013)	(0.011)	(0.120)	(0.019)	(0.038)	(0.014)
Obs	16,989	16,988	4,283	16,841	14,462	7,372
R^2	0.060	0.054	0.136	0.063	0.052	0.039
			t+1			
Credit_Exposure$_{i,t-1}$	-0.0052	-0.0433***	0.0489	0.0292 0	0.0707	0.0017
	(0.0192)	(0.0155)	(0.163)	(0.0292)	(0.0539)	(0.0197)
Obs	16,993	16,992	4,283	16,844	14,467	7,317
R^2	0.060	0.054	0.135	0.061	0.051	0.028
			t+2			
Credit_Exposure$_{i,t-1}$	-0.0027	-0.0086	-0.0678	0.0187	0.0131	-0.0087
	(0.0257)	(0.0189)	(0.0882)	(0.0376)	(0.0902)	(0.0286)
Obs	16,981	16,980	4,258	16,831	14,449	7,298
R^2	0.048	0.046	0.098	0.051	0.047	0.035

Authors' calculations. Dependent variables are measured as the log difference. Standard errors clustred by industry. The sample includes all years from 2004 to 2015. For employment we have information for only the second half of the sample, as per data availability from the Department of Labor. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. Similar to Berman, Martin and Mayer (2012) we include fixed effects by industry due to the heterogeneity between them in terms of productivity and pricing-to-market. Also, other authors such as Casas (2019) explain the heterogeneity by the difference in relative importance of intermediate inputs in production and Chen and Juvenal (2016) explore the heterogeneity based on the quality differences between industries.

Table 9—: Steady-state parameter values

Description	Parameter	Value	Target
Households			
Quarterly discount factor	β	0.983	Annualized deposit rate
Degree of habit formation	υ	0.815	Gertler and Karadi (2011)
Inverse Frisch elasticity of labor supply	φ	0.276	Gertler and Karadi (2011)
Banks			
Fraction of diverted bank loans	Λ	0.195	
Survival probability of bankers	θ	0.95	Survival duration of 5 years for bankers
Proportional transfer to the entering bankers	χ	0.009	
Goods-producing firms			
Elasticity of substitution	ϵ	4.167	Gertler and Karadi (2011)
Probability of keeping prices fixed	ψ	0.779	Gertler and Karadi (2011)
Share of effective capital	α	0.330	Gertler and Karadi (2011)
Capital-producing firms			
Depreciation rate of capital	δ	0.045	Investment-to-Capital ratio
Investment adjustment cost parameter	γ	1.728	Gertler and Karadi (2011)
Monetary authority and government			
Inflation coefficient of the Taylor rule	κ_π	1.5	Standard RBC value
Output gap coefficient of the Taylor rule	κ_y	0.125	Standard RBC value
Interest rate smoothing parameter	ρ_i	0.8	Standard RBC value
Debt feedback on taxes	κ_b	0.02	Kirchner and van Wijnbergen (2016)
Steady state values			
Banks' leverage ratio	ϕ	4	Elasticity of increasing marginal costs
Banks' credit spread	Γ	0.0330/4	Data
Steady state proportion of government expenditures	g/y	0.183	Data
Steady state government-debt-to-GDP ratio	b/y	1.8	Data
Steady state share of primary dealer debt	b^{prim}/b	1/4	Data

Table 10—: Business Cycle Statistics: Data vs. Model Economy

	Standard dev		Autocorrelations		Cross corr. to GDP	
	Data (1)	Model (2)	Data (3)	Model (4)	Data (5)	Model (6)
GDP (Y)	1.27	1.45	0.74	0.90	1.00	1.00
	(0.15)	[-1.23]	(0.23)	[-0.68]		
Consumption (C)	1.06	0.99	0.80	0.94	0.82	0.91
	(0.10)	[0.76]	(0.18)	[-0.77]		
Investment (I)	6.31	6.26	0.34	0.92	0.64	0.77
	(0.95)	[0.06]	(0.13)	[-4.36]		
Government spending (G)	4.96	3.79	0.68	0.67	0.35	0.13
	(1.14)	[1.03]	(0.31)	[0.00]		
Government debt	3.96	4.58	0.61	0.66	-0.38	0.16
	(0.44)	[-1.41]	(0.20)	[-0.26]		
CPI inflation	0.95	0.66	0.00	0.45	0.13	-0.23
	(0.08)	[3.82]	(0.06)	[-7.66]		
Policy rate	1.40	1.43	0.90	0.85	0.53	-0.82
	(0.19)	[-0.13]	(0.25)	[0.17]		
Credit spread	1.37	1.61	0.87	0.65	-0.52	0.17
	(0.15)	[-1.61]	(0.20)	[1.10]		
Bank credit	3.57	1.61	0.92	0.74	0.60	0.55
	(0.53)	[3.66]	(0.28)	[0.63]		
Bank capital	33.73	7.62	0.65	0.63	-0.05	-0.27
	(10.96)	[2.38]	(0.39)	[0.06]		

Columns (1), (3) and (5) report the data volatilities, autocorrelations and correlations with output, respectively. The data spans the period between 2000Q1 and 2020Q1. Remaining columns report the corresponding model moments of the 10,000 simulated time series. Round brackets show standard errors, whereas square brackets display the t-statistics. Cyclical components of both the model and the data are estimated using a HP filter with a smoothing parameter of 1600.

Table 11—: Effects of a surprise borrowing shock

	(1) Data	(2) Model
Capital (loan) decline (%)	1.00	1.00
Investment decline (%)	1.40	1.48
Wage decline (%)	0.81	0.33
Labor decline (%)	0.16	0.15
Welfare decline (%)	*n.a.*	0.083

The first column presents the results that are obtained in our empirical section. The second column presents our results from the DSGE model, in which the b^{prim} shock is normalized to 1% of GDP on impact with an autocorrelation coefficient ρ_b of 0.955.