

# The Real Effects of the Bank Lending Channel

Gabriel Jiménez Atif Mian José-Luis Peydró Jesus Saurina

This version: May 2020 (November 2014)

Barcelona GSE Working Paper Series Working Paper nº 1099

The Open Access published version ['The Real Effects of the Bank Lending Channel', Gabriel Jiménez, Atif Mian, José-Luis Peydró, Jesús Saurina, Journal of Monetary Economics, 2019] is available online at: https://www.sciencedirect.com/science/article/pii/S0304393219301126 DOI: https://doi.org/10.1016/j.jmoneco.2019.06.002

This article is licensed under a Creative Commons Attribution 4-0 International (CC-BY 4.0) (https://creativecommons.org/licenses/by/4.0/)

# The Real Effects of the Bank Lending Channel

Gabriel Jiménez Atif Mian

José-Luis Peydró Jesús Saurina<sup>\*</sup>

#### Abstract

We study bank credit booms, exploiting the Spanish matched credit register over 2001-2009. We extend Khwaja and Mian (2008)'s loan-level estimator by incorporating firm-level general equilibrium adjustments. Higher ex-ante bank real-estate exposure increases credit supply to non-real-estate firms, but effects are neutralized by firm-level adjustments for firms with existing banking relationships. However, higher bank real-estate exposure increases risk-taking, by relaxing standards of existing borrowers (cheaper, longer-term and less collateralized credit), and by expanding credit on the extensive margin to first-time borrowers that default substantially more. Results suggest that the mechanism at work is greater liquidity via securitization of real-estate assets.

*JEL codes*: E32, E44, G01, G21, G28.

Keywords: Bank lending channel, Real effects of credit, Credit supply booms, Real estate, Securitization.

\* Gabriel Jiménez is at Banco de España, email: gabriel.jimenez@bde.es; Atif Mian is at Princeton University and NBER, email: atif@princeton.edu; José-Luis Peydró is at ICREA-Universitat Pompeu Fabra, Barcelona GSE, CREI, Imperial College London and CEPR, email: jose.peydro@upf.edu; Jesús Saurina is at Banco de España, email: jsaurina@bde.es. We thank anonymous referees and Ricardo Reis for very helpful comments and suggestions. We also thank Michael Weber for excellent research assistance. We also thank seminar participants at Universitat Pompeu Fabra, University of Chicago, European Central Bank, MIT (applied), New York Federal Reserve, University of Michigan (Ross), Notre Dam, and University of California Berkeley and also Joshua Angrist, Xavier Freixas, Asim Khwaja, Daniel Paravisini, Amir Sufi and Jaume Ventura for helpful comments. José-Luis Peydró acknowledges financial support from project ECO2015-68182-P (MINECO/FEDER, UE) and the European Research Council Grant (project 648398). The results or views expressed in this study are those of the authors and do not necessarily reflect those of the Banco de España or the Eurosystem.

#### 1. Introduction

A large literature connects financial crises with collapsing credit and asset price bubbles.<sup>1</sup> A key mechanism linking such financial shocks to the real economy is the bank-lending channel which claims that financial shocks propagate to the real economy via banks' *credit supply* channel. This paper contributes to the bank-lending channel literature in two ways.

First, while the existing literature has largely focused on *negative* credit supply shocks, we focus our attention on credit booms, exploiting the boom in Spain fueled by real estate, global capital flows and securitization. Credit booms are the best predictors of crises,<sup>2</sup> and theory argues that the bank lending channel may be asymmetric in booms vs. busts. For example, an important subset of firms (such as large mature firms) may not be constrained at the margin during good times. Consequently, credit booms might lead to excessive risk taking on the extensive margin that portend future troubles (Dell'Ariccia and Marquez (2006), Shin (2009)). At the macro level, Guerrieri and Iacoviello (2013) show that occasionally binding collateral constraints drive an asymmetry in the link between housing prices and economic activity, where booms imply small real effects as compared to busts.

Second, to fully analyze the real effects of bank credit supply, including risk-taking, one needs detailed loan level data on both loan terms and volume during a full cycle as well as a firm-level estimator of credit supply. We use the excellent credit registry data from Spain that enables us to follow loan terms and amount for *all* loans originated by the banking sector over time. We analyze the effects of positive credit supply shocks on loan terms and quantity, and on the intensive versus extensive margin (e.g., as mentioned above, the extensive margin may be more crucial for positive credit supply shocks). Moreover, we augment the Khwaja and

<sup>&</sup>lt;sup>1</sup> The bank-lending channel literature has mainly relied on negative credit shocks to identify the bank lending (e.g. Bernanke (1983), Peek and Rosengren (2000), or the papers that followed the financial crisis in 2008).

<sup>&</sup>lt;sup>2</sup> See e.g. Schularick and Taylor (2012), Jordà, Schularick and Taylor (2013), Freixas, Laeven and Peydró (2015).

Mian (2008)'s (KM henceforth) fixed effect technique for identifying credit supply shocks at the loan level by estimating the otherwise unobservable covariance between bank-level (credit supply) shocks and firm-level (credit demand) shocks. We then use this covariance to construct an unbiased estimate of the *firm-level* impact of the bank lending channel that takes into account firm-level equilibrium adjustments. Our adjustment accounts for the possibility that the overall effect of a positive credit supply shock may be attenuated if firms reduce their borrowing from banks that do not receive a strong credit supply shock.

We use the comprehensive loan level data from the credit register of Banco de España, the bank supervisor. The data include loan level information for *all* bank loans granted at quarterly frequency in Spain, a bank dominated financial system, from 1999Q4 to 2009Q4, covering a whole credit boom. We match the credit register with administrative balance sheet variables for firms (from the mercantile firm register) and for banks (from Banco de España).

We find strong effects for the impact of ex-ante bank real estate exposure on credit supply to non-real-estate firms. We show that banks with more real estate related assets before the boom (as of 2000) increase the supply of credit during the boom to non-real-estate firms. Moreover, the effects are also economically large: one standard deviation increase in ex-ante exposure to real estate more than doubles the growth in credit supply to non-real-estate firms during the credit supply boom.

However, for the set of firms with multiple borrowing banking relationships at the start of the boom, the *firm-level* aggregate impact of credit supply is close to zero, despite a large loan-level impact of credit supply for these firms! Crowding out thus dramatically reduces the net impact of real-estate-exposure-induced credit supply on the *quantity* of credit supplied.

There is, however, a significant impact on the *price* of credit in the firm-level and loanlevel channel. We show that firms with unused lines of credit start to disproportionately favor banks with greater ex-ante real estate exposure, suggesting improved credit terms through a revealed preference argument. Consistent with this interpretation, we also find that higher exante bank exposure to real estate assets leads to a reduction in the rate of collateralization and a lengthening of loan maturity at the loan and firm-level. All these results suggest that ex-ante stronger bank real estate exposure leads to softer lending terms for non-real-estate borrowers in the intensive margin. Despite the zero-aggregate firm-level impact of bank-real-estate-induced credit supply channel on the *quantity* of credit, there could be some positive real effects through the softening on credit terms. However, we find *no* evidence of any significant impact on real firm outcomes, including firm sales or employment.

The results above are based on firms that already have borrowing relationships at the time of the credit boom. When we look at the effect of ex-ante bank exposure to real estate on the extensive margin of lending to new, non-real estate clients, we find a large effect on credit quantity. Growth in credit to new clients in the boom is much stronger for banks with greater ex-ante exposure to real estate. A one standard deviation increase in ex-ante exposure to real estate. A one standard deviation increase in ex-ante exposure to real estate. Importantly, new credit granted is substantially riskier for banks with higher ex-ante real estate assets, as it is about a third more likely to default.

There are several potential mechanisms that can lead banks with high real estate exposure to expand the supply of credit. These include: (i) the joining of Euro that lowered risk spreads for Spain may disproportionately benefit banks with high real estate exposure; (ii) boom in real estate prices; and (iii) strong capital inflows due to global financial innovation that enabled securitization of real estate assets. We check for the possible validity of these mechanisms. The positive credit supply shock identified in our paper is concentrated in the 2004-2007 period, which was a period of strong securitization and capital inflows. We do not find a significant credit supply effect in the 2000-2003 period even though Spain was already a member of the euro, and real estate prices were strongly rising.

There is further evidence that securitization of real estate assets associated to global liquidity helps banks expand credit supply due to greater provision of liquidity. In particular, we find that the credit supply effect is stronger for banks that faced tighter ex-ante liquidity constraints. <sup>3</sup> Liquidity constrained banks are banks that ex-ante borrow more from the interbank market or that ex-ante pay more for bank deposits. In contrast, there is no evidence that banks more capital constrained have stronger credit supply effect of real estate exposure.

Consistent with the view that the credit supply effect is driven by a relaxation in bank liquidity constraints as opposed to a relaxation in bank capital constraints, we find that there is no difference in our main effects regardless of whether a bank issues covered bonds or asset backed securities (ABS) to take advantage of securitization. Both covered bonds and ABS provide liquidity to banks, but only ABS provides capital relief to banks.

In summary, the credit supply boom leads to insignificant positive real effects at the firm level for firms with existing banking relationships, but to substantial higher bank risk-taking, both by softening credit terms for firms with established access to credit and by expanding credit to new clients that turn out to be considerably riskier ex-post. The expansion in credit therefore adds fragility to the financial system.

These results are consistent with models such as Shin (2009) and Dell'Ariccia and Marquez (2006) that suggest that an increase in credit supply to new marginal borrowers increases credit risk, and hence can be detrimental for financial stability. Our results are also consistent with models in which higher bank liquidity implies more risk-taking in bank lending due to moral hazard (see e.g. Allen and Gale (2007), Diamond and Rajan (2001)).

<sup>&</sup>lt;sup>3</sup> We thank an anonymous referee for suggesting these tests to pin down the mechanism at work.

Finally, we also analyze whether the 2008 collapse in the securitization market and foreign capital outflows imply a credit crunch. There is a sharp reversal in the loan-level bank lending channel. The firm level impact is more modest but economically and statistically significant in some quarters, different from the credit boom period.

Our main contribution to the literature is on analyzing the real effects of the bank lending channel in booms. Empirical papers use crisis shocks to study whether credit matters (Bernanke (1983), Peek and Rosengren (2000), or the recent large literature following the 2008 financial crisis); however, as the historical evidence summarized in Freixas, Laeven and Peydró (2015) shows, credit booms are the best predictors of financial crises. Moreover, there are theoretical reasons, as we argued above, why booms and busts may have important asymmetric effects for real effects. In fact, our results show no significant real effects at the firm level associated to credit supply booms, but strong bank risk-taking in booms with implications for financial stability.

Moreover, most papers in the literature analyze only credit outcomes of the bank channel, but not the real effects (Khwaja and Mian (2008), Paravisini (2008), Jimenez et al (2012, 2014)). We analyze firm-level effects by extending the KM framework. Indeed, our results reveal that while the bank transmission mechanism is strong, its aggregate (net) credit and real impact at the firm-level is substantially reduced due to the crowding out effects for large segments of the borrowers during booms. Many recent papers use the KM methodology in loan-level regressions to isolate credit supply. We extend the KM framework to study firmlevel effects. Papers using "natural experiments" identify real effects by exploiting credit supply shocks that are independent of economic fundamentals. However, as most crucial shocks to banks (e.g. crises, runs, monetary policy) are not "natural experiments", a key contribution of our paper is to identify the firm-level credit supply when firm (demand) and bank (supply) shocks are not orthogonal. The rest of the paper is organized as follows. Section 2 provides the empirical strategy and data. Section 3 presents the results, while Section 4 concludes, stressing policy implications.

#### 2. Empirical Strategy

This section provides the empirical strategy to estimate the firm-level (and loan-level) bank lending channel, including the KM extension and the matched firm-bank dataset (with comprehensive credit data matched with firm and bank balance sheet data).

#### 2.1 Framework

We follow the KM framework (see Khwaja and Mian (2008)) that have also been used in numerous papers to identify the credit supply effects at loan level (among many others, Schnabl (2012), Iyer et al. (2014)) and extend the KM technique to analyze the firm-level analysis, which we explain in this subsection.

Consider an economy with banks and firms indexed by *i* and *j* respectively. Firm *j* borrows from  $n_j$  banks at time *t* and assume (without loss of generality) that it borrows the same amount from each of the  $n_j$  banks. The economy experiences two shocks at *t*: a firm-level credit demand shock  $\eta_j$  that proxy for firm-level fundamentals and a bank-specific credit supply shock  $\delta_i$ .  $\eta_j$  reflects changes in the firm's fundamentals as for example productivity or customer demand shocks, or risk shock, which are all largely unobserved. Therefore, it represents unobserved firm-level fundamentals.  $\delta_i$  reflects instead changes in the bank's funding situation, such as a run on short term liabilities (a negative shock) or new opportunities to access wholesale financing (a positive shock). In this paper,  $\delta_i$  is the initial exposure to real estate assets of bank *i*.

Let  $y_{ij}$  denote the log change in credit from bank *i* to firm *j*. Then the basic credit channel equation in the face of credit supply and demand shocks can be written as:

$$y_{ij} = \alpha + \beta * \delta_i + \eta_j + \varepsilon_{ij}. \tag{1}$$

Equation (1) assumes that the change in bank credit from bank *i* to firm *j* is determined by an economy wide secular trend  $\alpha$ , bank (credit supply) and firm (credit demand) shocks, and an idiosyncratic shock  $\varepsilon_{ij}$ . While equation (1) is reduced form in nature, it can be derived as an equilibrium condition by explicitly modeling credit supply and demand schedules (see KM). We keep the analysis deliberately simple here to focus on the core estimation problem.

 $\beta$  if often referred to as the "bank lending channel", and we refer to it as the loan-level (local) lending channel in this paper. It can be estimated from (1) using OLS, giving us  $\hat{\beta}_{OLS} = \beta + \frac{Cov(\delta_i, \eta_j)}{var(\delta_i)}$ . The expression implies that as long as credit supply and demand shocks are significantly correlated,  $\hat{\beta}_{OLS}$  in (1) would be a biased estimate of the true  $\beta$ . For example, if banks receiving a positive liquidity shock are more likely to lend to firms that simultaneously receive a positive credit demand boost, then  $\beta$  would be biased upwards. KM resolve this issue by focusing on firms with  $n_j \ge 2$ , and absorbing out  $\eta_j$  though firm fixed-effects. The estimated coefficient  $\hat{\beta}_{FE}$  then provides an unbiased estimate of  $\beta$ .

However,  $\hat{\beta}_{FE}$  does not give us a complete picture of the net firm-level effect of bank lending channel on the economy. In particular, individual firms affected by some banks (in the loan-level channel due to a positive  $\beta$  in equation (1)) may seek alternative sources of bank financing to compensate for any loss of credit. Alternatively, if firms benefit from greater provision of credit via a positive credit supply shock to an individual bank, their borrowing from elsewhere may be cut either voluntarily or due to a crowding-out effect. What it matters for real effects is this firm-level credit availability. Thus, in order to gain a complete picture of the bank lending channel effect, one must compute its consequences at the aggregate firm level. We can do so by estimating the related firm-level version of (1):

$$\bar{y}_j = \bar{\alpha} + \bar{\beta} * \bar{\delta}_j + \eta_j + \bar{\varepsilon}_j.$$
<sup>(2)</sup>

 $\bar{y}_j$  denotes the log change (*t*+1 over *t*) in credit for firm *j* across *all* banks. It is not a simple average of  $y_{ij}$  from (1) since a firm can start borrowing from new banks as well in the extensive margin (potentially a key margin for firms' adjustment of credit supply shocks).  $\bar{\delta}_j$ denotes the average initial exposure to real estate assets of banks initially lending to firm *j* at time *t*, i.e.  $\bar{\delta}_j = \sum_{i \in N_j} \frac{\delta_i}{n_j}$  where  $N_j$  represents the set of banks lending to firm *j* at time *t* and  $\bar{\varepsilon}_j$ is an idiosyncratic error term.<sup>4</sup> The same firm-level fundamentals shock  $\eta_j$  appears in both equations (1) and (2) under the assumption that the shock on firm fundamentals equally affects a firm's borrowing from all banks. Note that this shock is about firm fundamentals such as unobserved risk or productivity shocks.

The aggregate impact of credit supply channel is captured by the coefficient  $\overline{\beta}$ , which we refer to as the firm-level aggregate lending channel. If there is no adjustment at firm-level in the face of bank-specific credit channel shocks, then  $\overline{\beta} = \beta$ . However, if there is some adjustment at firm-level, e.g. a crowding-out effect, then  $\overline{\beta}$  should be lower (in absolute value) than  $\beta$ . In the limit case, that firms can adjust perfectly their sources of finance, then in the initial time *t* the current banks' shocks  $\overline{\delta}_i$  is not binding for them, and hence  $\overline{\beta} = 0$ .

How does one estimate  $\overline{\beta}$ ? An OLS estimate of (2) yields  $\hat{\beta}_{OLS} = \beta + \frac{Cov(\delta_i, \eta_j)}{Var(\overline{\delta}_j)}$ .<sup>5</sup> While the variance of  $\overline{\delta}_j$  can be estimated in data (banks' initial real estate assets), the covariance term between unobserved firm (credit demand) and bank (credit supply) shocks is unobservable to the econometrician. However, a unique advantage of the preceding fixedeffects estimator at loan level is that it allows us to back-out the covariance term. Since  $\hat{\beta}_{FE}$ is an unbiased estimate of  $\beta$ , we can write  $Cov(\delta_i, \eta_j) = (\hat{\beta}_{OLS} - \hat{\beta}_{FE}) * Var(\delta_i)$ , where

<sup>&</sup>lt;sup>4</sup> Of course, if within the banks lending to the firm previous to the shock, there is heterogeneity in loan volumes, then one should weight the different bank specific shocks by the amount each bank lent to the firm.

<sup>&</sup>lt;sup>5</sup> This follows from  $Cov(\overline{\delta}_j, \eta_j) = Cov(\sum_{i \in N_j} \frac{\delta_i}{n_j}, \eta_j) = Cov(\delta_i, \eta_j).$ 

the variance of bank (credit supply) shocks  $\delta_i$ , can be estimated directly from data. Thus the firm-level aggregate lending channel effect,  $\overline{\beta}$ , can be estimated as:

$$\hat{\bar{\beta}} = \hat{\bar{\beta}}_{OLS} - \left(\hat{\beta}_{OLS} - \hat{\beta}_{FE}\right) * \frac{Var(\delta_i)}{Var(\bar{\delta}_j)}$$
(3)

The second term on the right hand side of (3) is the adjustment term that corrects for any bias in the OLS estimate of (2). The adjustment term corrects for the otherwise unobserved covariance between bank (credit supply) and firm (demand) shocks. The extra variance term in the denominator corrects for the fact that the variance of bank shocks averaged at the firm level may be different from the variance of bank shocks overall. Note that if the bank shock is independent of the firms, like in a natural experiment for bank shocks, then the OLS firm-level coefficient provides the firm-level aggregate bank lending channel.

Equation (3) is simple and practical to implement, as loan level credit register data are now available in most countries of the world (there are at least 129 countries with either public or private credit registers, see e.g. Djankov, McLiesh and Shleifer (2007)). The procedure can be summarized as follows. For any given bank shock  $\delta_i$  that is suspected of generating a bank transmission channel, run OLS and FE versions of (1) to estimate  $\hat{\beta}_{OLS}$  and  $\hat{\beta}_{FE}$  respectively. Then estimate firm level equation (2) using OLS to generate  $\hat{\beta}_{OLS}$ . Finally plug these three coefficients in (3) to estimate the unbiased impact of credit supply channel at the firm level.

We also perform some robustness for our KM extension. Our extension uses simplifying assumptions to keep the analysis tractable. Real world data may not satisfy some of these assumptions. How robust is equation (3) to such perturbations? Since close-form solutions are not possible with more generic assumptions, we present numerical solutions to the model under alternative scenarios. Table I of Online Appendix summarizes the results of our simulation exercise. Panel A takes our baseline scenario, i.e. the model presented above, and calibrates it using different assumptions on two key parameters of interest: the (unobservable)

correlation between firm (credit demand) and bank (credit supply) shocks ( $\rho$ ), and the extent of firm-level adjustment to bank transmission shocks ( $\Lambda$ ).  $\Lambda$ =100% implies there is full adjustment at the firm-level making  $\overline{\beta}$  =0. The calibration exercise assumes that true  $\beta$ =0.5 shocks are normally distributed with mean zero and variance equal to 1.0, and the variance roughly reflects the variance for firm-level credit changes from 2004Q4 to 2007Q4.

The results show that while OLS estimate  $\hat{\beta}_{OLS}$  and  $\hat{\beta}_{OLS}$  can be significantly biased with high absolute levels of  $\rho$ , our fixed-effects and bias-correction procedure in (3) successfully backs out the true coefficients of interest. The baseline analysis assumes that banks continue to lend to firms after realization of shocks. This may not happen in practice. Some loans may be dropped (terminated credit relationships) for idiosyncratic reasons and others due to either credit supply or credit demand shocks. Our OLS and FE regressions from the preceding section ignore such dropped loans. Do ignoring dropped loans change the results in Panel A? We test this by simulating dropped loans and then running our estimation procedure on surviving loans. Add a first-stage before our estimation procedure that drops some loans from our sample depending on the loans' firm (credit demand) shock, the bank (credit supply) shock, and an idiosyncratic factor. The probability of a loan getting dropped is modelled as a probit, with weights on various factors chosen to match what we find in data.<sup>6</sup> We then rerun our estimation procedure on the remaining sample. The results in Panel B show that our estimate of betas remains valid even when conditioning on loans that do not get dropped.

## 2.2 Datasets and Institutional Details

Another crucial aspect of the identification is the exhaustive credit data matched with precise firm- (and bank-) level balance-sheet data. Our data come from loan level credit

<sup>&</sup>lt;sup>6</sup> We set these parameters such that the coefficient on supply shock is -0.25 (as we will see in column (7) of Table V). The coefficient on demand shock is also assigned the same magnitude. Finally, the level effect is chosen such that about a third of total loans are dropped, as in our Spanish data. Our model also assumes that each firm borrows the same amount initially from its set of lenders. We also tested for robustness of our results to this assumption by simulating borrowing across banks by a firm that matches our data.

register of Banco de España, which is also the banking supervisor in Spain. It covers *all* loans to *all* non-financial firms. For computational purposes, we restrict to loans with an average borrowing of at least  $\epsilon$ 60,000, though results are identical with the whole sample. We further restrict the data to *non real-estate* loans in order to analyze the impact of bank exposure of real estate assets on loans to non-real estate firms (results are stronger with real estate firms).

We match each loan to selected firm characteristics (firm identity, industry, location, the level of credit, size, number of employees and sales) and to bank balance-sheet data. Both loan and bank level data are owned by Banco de España in its role of banking supervisor. The firms' dataset is available from the Spanish Mercantile Register, which is administrative data, at a yearly frequency (and represents 70% of outstanding bank loans from the CIR).

The credit data come at quarterly frequency and cover the period from the fourth quarter of 1999 to the fourth quarter of 2009. The 10-year coverage has the advantage of covering the full credit boom in Spain. There are 487,090 firms borrowing from any of a possible of 215 banks during this time period. To avoid data management issues due to large size, we randomly sample 10% of the firms based on the random penultimate digit of the firm fiscal identity number (though results are identical with the whole sample). Once a firm is selected, we keep all of its loans over the 10 year period in our sample. Our 10% random sample consists of 48,709 firms. While a firm may have multiple loans from the same bank at a point in time, we aggregate loans at the firm-bank-quarter level which forms our unit of analysis. Thus a "loan" in this paper refers to firm-bank pair.<sup>7</sup> There are 246 banks at the beginning of sample period and 214 banks by our sample's end. However, major bank mergers (in terms of

 $<sup>^{7}</sup>$  Firms can enter and exit the sample during our sample period. The average tenure of a firm in our sample is 25.7 quarters (out of a possible of 41 quarters), with a median tenure of 26 quarters and 25th and 75th percentile of 14 and 41 quarters respectively. The distribution of bank credit across firms is highly skewed with top 10% of firms borrow 75.3% of total credit in the economy (Online Figure 1, top-left panel). The skewed nature of firm-size distribution is typical around the world. The dotted line in the top-left panel of Figure 1 shows that the cumulative distribution function of credit across banks is very similar to the CDF picture for firms. As with firms, the top 10% of banks dominate the credit market.

size) happen before 2001Q4. Therefore, to keep a more consistent panel, we focus on the period 2001Q4 till 2009Q4 in our analysis (if a bank is acquired by another one, its loan portfolio shows up in the portfolio of the acquiring bank). Since our core variation of interest occurs around 2005, starting in 2001Q4 does not constrain our analysis.

There is a sharp increase in the growth of bank credit in 2004 followed by sudden stagnation in 2008 when the global financial crisis hits (see the top-right panel in Online Figure 1, which plots the total cumulative bank credit over time.). One of our aims in this paper is to test the extent to which the boom in credit supply can be attributed to an aggregate shock such as the Euro entrance, lower risk premia, boom in real estate prices, strong capital inflows or the rise in securitization.

Table I presents summary statistics. There are 29,848 firms taking out 67,838 loans in the fourth quarter of 2004. Since the KM and our extension relies on firms with at least two banking relationships, Table I also presents summary statistics for this subset of firms. There are 15,697 such firms taking out 51,397 loans. While about half the total firms have multiple banking relationships, they represent 89% of total firm credit in the economy (see Table II of the Online Appendix). The average loan size is  $\in$ 288,000 and the average firm borrows a total of  $\in$ 662,000 from the banking sector. 1.9% of loans are in default as of 2004Q4. However, there is a sharp increase in defaults in 2008 and, by the end of 2009, almost 8% of loans are in default (Online Figure 1 bottom-left panel). Moreover, the lower-right panel in Online Figure I plots Spanish house prices over time. There is a sharp increase in the growth of house prices beginning in 2001 that runs until 2007 when the global recession kicks in.

One of our key variables at bank level is a bank's exposure to real estate related assets at the beginning of our sample period. This variable is constructed as the share of total bank loans that go to the real estate sector (residential mortgages as well as loans to construction and real estate firms). The average exposure to real estate sector is 44% with a standard deviation of 15.7%. Finally, we also have information at the loan level on total loan commitments, credit drawn, whether the loan is collateralized by an asset and the maturity of the loan. For the summary statistics of all the credit, firm and bank variables, see Table I.

There is no counterpart to Freddie Mac and Fannie Mae in Spain. Consequently all mortgage loans are held by banks on their books in the beginning of our sample period when there is negligible securitization. This helps to explain the high share of real estate loans on banks' books in Spain. Another difference from the U.S. is that mortgage loans in Spain have full recourse to the borrower. Banks in Spain can be classified in two broad categories: commercial banks and savings banks. Out of the 192 banks in 2004Q4 for which we have financial information are 46 savings banks representing 41.9% of total bank assets. Commercial banks are traditional banks (including foreign banks) that have shareholders as owners of the bank. Savings banks on the other hand rely on a general assembly for governance, consisting of representatives of depositors and government. The general assembly elects a board of directors who look for a professional manager to run the banking business. Commercial banks profits can either be retained as reserves or pay out as dividends. For the savings banks, the profits are either retained or paid out as social dividend (i.e. to build and run educational facilities, libraries, sport facilities, pensioners clubs and so on where the savings banks operate). However, despite their differences in governance structures, both commercial banks and savings banks operate under the same regulatory framework and compete against each other in common markets.<sup>8</sup>

Table II tests whether banks with high real estate exposure are systematically different. The top panel regresses various bank characteristics against banks' exposure to real estate assets and reports the coefficient on real estate exposure. Banks with more real estate

<sup>&</sup>lt;sup>8</sup> Historically, savings banks have focused on households and engaged in providing mortgage and deposit facilities. Commercial banks, on the other hand, have been more dominant in lending to the corporate sector. However, there has been considerable convergence in the scope of the two types of banks since liberalization began around mid-seventies. As of 2019, these type of banks have basically all converted into commercial ones.

exposure as of 2000Q1 are similar to other banks in terms of size, profitability (return on assets), risk (non-performing loans) and capital ratio. Moreover, they have similar behaviour until the stronger credit boom kicks in 2004-07; however, after the shock, banks with higher ex-ante real estate increase more lending and total assets (see also Online Figure 2). In addition, for reasons already highlighted, banks with real estate exposure are more likely to be savings banks. This implies that in some regressions we will control for savings banks in a non-parametric way (with firm\*bank-type fixed effects), and in some robustness regressions, we will exclude savings banks from the regressions.

The middle panel tests whether firms borrowing from banks with high real estate exposure are systematically different. Since a firm may borrow from multiple banks, we take the average of initial real estate exposure for banks lending to a given firm. We find that firms borrowing from banks with higher real estate are smaller in size, have higher tangible assets to total assets ratio (more likely to be collateralized), and are less likely to borrow short term. Hence, bank-level evidence is not enough to identify the bank lending channel, and loan-level data with firm fixed effects may be necessary (and even in some cases firm\*bank-type fixed effects and some loan controls for robustness). Finally, the bottom panel tests if loan level outcomes as of 2000 differ. While there is no difference in default rates, there are some loan differences, notably volume. However, as the right-lower panel shows, conditional on lending to the same firm, amount does not differ across banks with differential real estate exposure.

## 3. Estimating the Bank Lending Channel

In this section we provide and then discuss the main results of the paper.

#### 3.1 Loan-Level Bank Lending Channel Estimates

We regress change in credit from 2004Q4 to 2007Q4 against a lender's initial exposure to real estate assets. Column (1) of Table III estimates equation (1) without firm fixed effects. In

line with the bank-level results of Online Figure 2, there is a strong association between loan growth and a bank's initial exposure to real estate assets. Can we attribute this correlation to a credit supply effect? Since we need firm-fixed effects to answer this question, we limit ourselves to firms with multiple banking relationships as for 2004Q4 (almost 75% of all firms borrow from at least two banks during our sample period). Column (2) restricts sample to such firms with results similar to column (1), thus suggesting that the results in this paper are not different between firms with multiple and single bank relationships.

Column (3) adds firm fixed effects. The coefficient on bank real estate exposure (0.386) implies that a one standard deviation increase in real estate exposure generates a 6.1 percentage points higher growth in credit supply. This is more than a doubling of the average loan-level credit growth rate of 5.7% between 2004Q4 and 2007Q4. Since real estate exposed banks tend to grant longer term and more collateralized loans, there may be a residual concern that our results are driven by differences in the types of loans extended by real estate exposed banks (e.g. the credit boom was driven by greater demand for longer term loans which happen to be the specialization of real estate exposed banks). Column (5) controls for a loan's collateralization rate and maturity as of 2004Q4 as well as changes in these variable between 2004Q4 and 2007Q4. There is no change in the coefficient of interest.

Finally, we know that savings banks are more likely to have high real estate exposure. Could our results thus far be described as a savings banks phenomenon? We address this issue in column (4) by excluding savings banks and in column (6) by including bank-type *interacted* with firm fixed effects, where bank-type is either "commercial" or "savings banks". These regressions directly exclude savings banks or force comparison across loans of the *same* firm within the *same* bank-type. Our coefficient of interest is almost identical and even higher in column (6). Finally, column (7) shows a similar coefficient when we control for other bank characteristics such as NPLs, size, profits, capital and liquidity.

Columns (2) through (7) go through a strong battery of tests to isolate the supply side transmission channel driven by a bank's exposure to real estate.<sup>9</sup> Firm fixed effects, loan level controls, bank controls and bank-type interacted with firms fixed effects control for credit demand shocks in a nonparametric way. The strong power of controls can be gauged from the fact that R-square goes to 0.003 in column (2) to 0.64 in column (7) *without* any decrease in the coefficients' magnitude! The persistence of a coefficient despite a substantial increase in regression R-square due to controls provides a strong support for exogeneity of the right hand side variable of interest. Moreover, there is not statistically difference between the OLS and fixed effect coefficient, as the real estate bank shock is uncorrelated with firms' fundamentals in *non real-estate* firms. Finally, there may be a remaining concern that our results are driven by some pre-existing trends in data. Column (8) tests for this by repeating our core specification over the period 2001Q4 to 2004Q4. The estimated coefficient turns out to be negative, small (1/3 of the subsequent period), and statistically indifferent from zero.

A downside of the dependent variable we have used thus far (the "intensive margin") is that we cannot compute change in loan amount for loans that are dropped (terminated) before 2007Q4. In order to take such "dropped loans" into account, we construct an indicator variable that is 1 if a loan exists in 2004Q4 but not in 2007Q4, and 0 if it exists in both quarters. Column (9) repeats our core specification using "loan dropped" as dependent variable (i.e. the "extensive margin of dropped loans"). The number of loans increases in column (7) from 32,647 to 51,397 because of the inclusion of *all* outstanding loans in 2004Q4 regardless of their status in 2007Q4. Consistent with our earlier results, banks with higher real

<sup>&</sup>lt;sup>9</sup> Other robustness tests we have run are: controlling for the average real estate exposure of other banks lending to the same firm, and, controlling for firm observables in firm level regressions where firm fixed effects are not possible (this only for the firm-level aggregate channel). Results are very similar. In the main regressions at the loan level we also double cluster the standard errors at both firm and bank level. Other controls are different demand trends by groups of companies (according to firm sector at 2 digits, province or size) and by groups of banks (according to their main sector of specialization or province). Moreover, loan applications show that there are no higher loan applications in 2004-07 from non-financial firms to banks with higher real estate assets. See Online Appendix for some of these robustness checks.

estate exposure are *less* likely to drop (terminate) a loan. Column (10) uses a Tobit specification to combine the "intensive margin" effect of column (3) and the "extensive margin" result of column (9).<sup>10</sup> The combined effect of the two margins, not surprisingly, makes the overall impact in the credit channel even stronger.

#### 3.2 Firm-Level Aggregate Credit Estimates

Column (11) presents the OLS (and potentially biased) estimate of firm-level credit channel coefficient. The coefficient is close to zero and statistically not different from zero. The unbiased estimate of firm level credit channel is given by equation (3), which adjusts the coefficient in column (11) to take into account endogenous matching of firms with banks. Since the adjustment term depends on the differences between loan level OLS and fixed effect estimate, it is going to have a small effect in our case. The adjustment term is equal to (0.40-0.386)\*0.025/0.0123, i.e. 0.037. The unbiased firm-level bank lending channel effect is thus equal to -0.020 (see also Table IX). It turns out that despite a very strong credit supply channel effect at the bank level, the *net* firm-level impact is close to zero! Note also that non-bank sources are unlikely to play a significant role in our analysis since the net impact is close to zero with only bank sources alone (moreover, there are also no real effects in firm outcomes as we will see later).

Our result thus highlights the importance of incorporating firm level adjustments in the analysis of the credit supply channel. A simple correlation – *or even causation* – between bank credit extension and bank liquidity shocks can be highly misleading at the loan (bank-firm) or bank level. The speed at which firm-level borrowing adjusts also points towards a dynamic banking system in good times where borrowing relationships are created and destroyed at regular frequency. Consistent with this view, we find that about 45 percent of

<sup>&</sup>lt;sup>10</sup> In the Online Appendix we show the results with another measure that combines both margins of lending (change in credit over half of the initial plus final level of credit).

firms during our sample period break away an existing banking relationship *and* start a new banking relationship with a *different* bank afterwards.

The regressions in Table III focused on the 2004Q4 to 2007Q4 period, which is the heart of credit boom in Spain. Since the underlying data are quarterly and span a much longer time horizon, we can replicate our estimates at a quarterly frequency over the entire period. We anchor 2004Q4 as our reference quarter, and use  $\Delta \log (credit)$  between quarter *t* from 2001Q4 to 2009Q4. We estimate the OLS and FE regressions corresponding to columns (2) and (3) of Table III respectively and plot the corresponding coefficients on bank exposure to real estate in Figure 1 (see also Online Appendix). These coefficients capture the evolution of loan-level bank lending channel in Spain. Both OLS and FE estimates are close to zero until 2004Q4 and statistically not different from zero.<sup>11</sup> Thus the credit channel documented in Table III is not driven by any pre-existing trend, as we found earlier for the overall pre-shock cross-section (i.e., there is no differential credit growth to 2004Q4 for loans granted by banks with greater real estate exposure. This finding also suggests that our earlier results are not driven by boom in house prices or by the euro entrance with also the lower risk premia.<sup>12</sup>

Our results indicate that once securitization market (and capital inflows) are strong enough in terms of volume and is sustained over a long enough period, banks begin to rely on the newly found source of liquidity and start lending against it. The bank lending channel effect of securitization builds gradually over time until 2008, when the private market for securitization shuts down and there are capital outflows. Once the global financial crisis

<sup>&</sup>lt;sup>11</sup> Standard errors are not reported for brevity, but are similar to those shown in corresponding tables. The OLS and FE estimates track each other quite closely in Figure 3. Since the FE estimate absorbs credit demand shocks at the firm-level, the compliance between OLS and FE estimates show that firm (credit demand) shocks during our sample period are largely orthogonal to bank (credit supply) shocks driven by exposure to real estate assets.

<sup>&</sup>lt;sup>12</sup> As Online Figure 1 shows, the growth in house prices were as strong during the 2001-2004 period as the 2004-2007 period. If the credit channel effect in Table III was driven by real estate exposed banks' loan assets appreciating in value, we should see a similar effect over 2001 to 2004. As we will discuss later in detail, the fact that results are not significant in 2001-04 but only in 2004-07 suggests that the loan-level bank lending channel effects are driven by the boom in securitization (and the strong capital inflows) that kicks into high gear between 2004 and 2007 (see Panel B of Online Figure 1).

begins in fall of 2008, the bank lending channel in Spain turns *negative*: Banks with greater ex-ante exposure to real estate assets cut credit at a faster pace than during the crisis.

Figure 1 Panel B (see also Online Appendix) replicates firm-level OLS estimate of column (11) in Table III, but replaces the dependent variable with log change in firm credit between quarter *t* and 2004Q4. As in Figure 3, we plot the OLS coefficient separately for each *t* from 2001Q4 to 2009Q4. Since loan-level OLS and FE estimates are close to each other, OLS and bias-corrected coefficients do not differ significantly either. The bias-corrected coefficients in Figure 1 reflect the net firm-level impact of bank lending channel over time. The net impact in 2004Q4-2007Q7 period is zero despite the strong the loan-level results. Therefore, in booms we do not observe a firm level impact on credit supply, whereas in the crisis, the effects are significant at the firm level, with a reduction of 15% in credit supply in 2009, which implies an important asymmetry between booms and busts for firm level aggregate.

#### 3.3 Other Credit Terms and Conditions

What about other credit terms and conditions? Greater willingness by banks to extend credit supply could lead to greater competition, hence putting downward pressure on other credit terms. While we do not observe loan rates, we know the fraction of loan commitment that is drawn down by a borrower as well as loan maturity and collateralization rate. Changes in loan draw-down rate (drawn credit over total commitment) during the credit boom give us useful information on the otherwise unobserved terms of credit (such as covenants and interest rates). This idea is based on a revealed preference argument. As banks compete more aggressively for a firm's business, the firm should prefer to draw down more aggressively from the bank with better loan terms.

Columns (1) through (3) in Table IV test if the draw-down ratio goes up faster during 2004Q4 to 2007Q4 for banks with greater exposure to real estate. Column (1) runs our core

specification on data restricted to multiple relationship firms as of 2004Q4. There is a strong effect of bank real estate exposure on growth in drawn-down rate. A one standard deviation increase in bank's real estate exposure increases the drawn-down ratio by 1.33 percentage points. The increase in drawn-down ratio could have resulted from declining loan commitments. However, as we have already seen in Figure 3, banks with greater real estate exposure are increasing their loan commitments at a faster pace during 2004-2007 period. The increase in draw-down ratio happens *despite* faster growth in loan commitments from real-estate-exposed banks; hence, it points towards better loan terms offered by these banks.

Column (2) shows that the increase in drawn to commitment ratio is not driven by real estate exposed banks making different types of loans, i.e. we control for maturity and collateral (e.g. if real estate exposed banks granted shorter maturity loans during the time period, such loans are naturally going to have higher drawn to commitment ratio). Column (3) further adds firm fixed effects. Our coefficient of interest remains identical in both columns.

A direct measure of credit terms in our data is the fraction of loans that are collateralized. Columns (4) to (6) show that credit terms are relaxed over 2004-2007 by banks with more real estate exposure by reducing rates of collateralization (notably when we control for other loan variables or firm fixed effects). The inclusion of controls for loan maturity is necessary when testing for differences in collateralization change for two reasons.<sup>13</sup> First, as we saw in Table II, real estate exposed banks are more likely to have longer maturity loans which naturally have higher rates of collateralization. Second, and more importantly, the *change* in propensity to make longer term loans (Columns (6) to (9)) is also stronger for banks with real estate exposure. Hence, as done in Column (5), it is crucial to control for loan maturity and changes in loan maturity when comparing differences in collateralization rates.

<sup>&</sup>lt;sup>13</sup> Online Figure 5 plots the quarter-by-quarter coefficients for drawn-to commitment and collateralization rate. The sharp increase in drawn to commitment ratio for real estate exposed banks kicks in around 2005 (before there is no differential effect). Results (though weaker) hold for collateralization rate as well.

#### 3.4 Bank Heterogeneity: Liquidity and Capital Channels

We want to understand better the mechanism by which higher exposure to real estate can imply higher credit supply in 2004-07. What friction was preventing loan supply from expanding previously? The literature typically points to agency problems that make external finance costly for banks to raise. There are two main potential channels. First, the binding the constraint could be bank capital requirements. That is, equity is the costly input that banks are economizing on. This suggests that the effect of the 2004-07 shock to be largest for banks that initially had low capital ratios. Alternatively, it could be that deposits are the costly input that banks are economizing. In this case, we might expect the effect of the 2004-07 shock to be largest for banks that initially had high costs of raising uninsured deposits.

To test the two hypotheses, we use the benchmark model of Table III (and IV) and analyze the effects that some bank characteristics related to ex-ante bank liquidity and capital have on credit outcomes depending on the ex-ante exposure of the bank to real estate. The results are shown in Table V. We introduce the interaction of real estate exposure with the log of total assets, the capital ratio, the interbank ratio (lending minus borrowing in the interbank market), and with ROA, which are the bank variables we use as bank controls, and add two additional ones on liquidity and capital, which are bank deposit rate and bank NPLs.

Overall we find strong evidence that the main channel at work is bank liquidity. The impact of bank real estate exposure on the softening of standards is stronger for banks which are ex-ante liquidity constrained (which we proxy for either banks that ex-ante borrow more from the whole interbank market or that ex-ante pay more for deposits; note that these two variables are highly correlated: -57%). Results on bank capital are not robust and, differently from bank liquidity, different components of bank capital (capital ratio, profits which is the main determinant of change in bank capital and NPLs) have different signs and are not robust.

#### 3.5 Extending Credit to New Clients

So far our core analysis was based on loans outstanding in 2004Q4, which were followed forward in time. The question remains whether higher bank liquidity led to a net increase in credit for new borrowers. A shift in the supply of bank credit should make banks more willing to lend to riskier firms on the extensive margin (see e.g. Shin (2009) or Dell'Ariccia and Marquez (2006)). These firms may have been denied credit in the past, but with bank liquidity expanding the supply of credit, they have a better chance of getting a loan.

Table VI tests whether banks with greater real estate exposure lend more to new clients on the extensive margin. We define "new credit" as credit given to first-time clients between 2004Q4 and 2007Q4 and regress the log of total new credit against a bank's initial exposure to real estate assets. We find that banks more exposed ex-ante to real estate are significantly more likely to make loans to new clients on the extensive margin (Column (1) shows this; Column (2) replaces credit drawn with new total credit commitments with similar results).

Column (3) normalizes new credit outstanding by total assets of the bank. The estimated coefficient implies that a one standard deviation increase in real estate exposure is associated with an increase of bank lending by 10.4 percent more of its assets to new clients. New bank clients can be of two types: firms that never borrowed from any bank in the past, and firms that start borrowing from the given bank for the first time after 2004Q4. If we split these two types by only focusing on lending to firms that never borrowed from any bank in the past. The coefficient drops to 0.38 from 0.665, showing that more than half of our extensive margin result is driven by lending to firms that did not borrow from any bank in the past.<sup>14</sup>

<sup>&</sup>lt;sup>14</sup> Online Figure 6 plots the quarter-by-quarter estimates of columns (3) and (4). The differential growth in new credit continues until 2008, before collapsing as the financial crisis kicks in. The extensive margin regressions are run at bank level and hence suffer from unobserved credit demand shocks. We cannot use our firm fixed effects approach, however, our earlier results show that the estimated covariance between firm (credit demand) and bank (supply) shocks for firms borrowing from multiple banks in 2004Q4 was close to zero. Hence it is reasonable to assume that similar correlation holds on the extensive margin as well.

Column (4) shows that new credit driven by exposure to real estate assets is significantly more likely to default by the end of 2009. A one standard deviation increase in bank exposure to real estate is associated with 1.03 percentage point increase in default rate for new credit.

#### 3.6 Securitization and Foreign Capital Inflows Channel

The results so far suggest that ex-ante exposure to real estate assets increases the supply of credit to non-real-estate firms in 2004-07, but not before. Moreover, effects are stronger for illiquid banks. Therefore, given the timing and the mechanism at work, results point out to the securitization and capital inflows boom in 2004-07 (see also Online Figure 1, Panel A and B),<sup>15</sup> and also capital inflows (global liquidity) and securitization provide banks with higher liquidity to expand the supply of credit. In this section, we further explore securitization.

We use the term "securitization" for issuance of both covered bonds and asset-backed securities by banks in Spain. While the two securities differ in some aspects, they share the basic characteristic of allowing banks to access liquidity by pledging their real estate assets and, therefore, allowing them to increase credit supply. Spanish banks were the second largest issuers of both covered bonds and ABS in Europe. Covered bonds are backed by a portfolio of real estate collateralized loans with a loan-to-value ratio of at most 80%; banks can only issue covered bonds up to 80% of the total value of the underlying backing pool of collateralized loans; and they also provide recourse to the issuing bank if needed. Thus covered bonds' purpose is the provision of liquidity for banks. There is no capital advantage for issuing covered bonds and these bonds remain on a bank's balance sheet.

<sup>&</sup>lt;sup>15</sup> The issuance of non-GSE ABS and subprime MBS in the U.S. rose dramatically during 2004 to 2007 (see e.g. Adrian and Shin (2009)). Securitization was driven by a series of global factors, such as global imbalances and soft monetary policy in U.S. and Europe (see also Maddaloni and Peydró, 2011). The rise in securitization was not limited to the U.S. Countries with characteristics similar to the U.S. (large current account deficits and a housing booms) also saw a rise in the issuance of mortgage-backed securities, e.g. Spain. In the case of Spain, most buyers were from other Euro Area countries, notably Germany though they were also from Asia.

Asset backed securities (ABS) are issued by selling a portfolio of loans (usually mortgages). In Spain the originating bank is usually the servicer of loans as well. Thus one important difference between covered bonds and ABS is that ABS allows banks to transfer some credit risk out of their balance sheet. However, in certain cases, banks provide "credit enhancement" to an ABS, thus promising to absorb a certain percentage of the first losses in case of default. The accounting rules in Spain instructed banks to keep ABS on their balance sheets if they retain some component of credit risk.

The effect of securitization is not uniform across all banks. Since securitization depends on real estate assets, banks with greater exposure to real estate assets before the securitization boom are impacted more. This result is confirmed by columns (1) through (3) of Table VII.<sup>16</sup> Columns (1) and (2) present the bivariate relationship in un-weighted and weighted (by bank assets) regression. The correlation between real estate exposure and securitization at the bank level is strong and highly significant. Since there is negligible securitization in the beginning of 2000s, an equivalent test for new securities issued is to regress the stock of securities issued by 2007 against initial real estate assets. This is done in column (3) and the correlation becomes even stronger.

Moreover, access to liquidity due to securitization also lead banks to extend more credit (as confirmed in the last two columns of Table VII). Though our paper is on the effects of real estate exposure, with several caveats,<sup>17</sup> we also present in Table VIII the results instrumenting

<sup>&</sup>lt;sup>16</sup> This is also confirmed in Online Figure 8 that plots the change in securitized assets between 2004 and 2007. Online Figure 7 plots the aggregate issuance of securitization in Spain over time. It was close to negligible in the early 2000s; however, in 2004 there was a strong increase and by 2008, the stock of securitized assets represents 29.9% of total bank credit. Securitization (i.e. issuance of ABS and covered bonds) provided a novel opportunity for banks to use their real estate assets as collateral for wholesale financing, thereby increasing credit supply.

<sup>&</sup>lt;sup>17</sup> We use real estate loan share rather than a direct measure of securitized assets for five reasons. First, there could be indirect channels by which real estate exposure could affect credit other than securitization (though we control for other key bank variables and Table II suggests that the differences between banks with different real estate exposure are only important after the 2004 shock). Hence, the exclusion restriction may not be satisfied. Second, securitization may be just the mechanism by which foreign capital inflows provide the liquidity for banks to increase credit. Third, data on securitized assets is not available for some banks whereas real estate exposure is available for all banks. Fourth, what matters most for credit channel is the ability and expectation of

actual securitization (both total securitization and ABS of mortgage assets) by the ex-ante real estate exposure in a two-stage regression. We analyze changes in credit volume and terms. The first stage shows that ex-ante real estate exposure is highly correlated with actual securitization. The F of the excluded instrument is higher than 16 (i.e., it does not suffer from weak instrument problems). We also control in some columns for the main observable bank characteristics, for other loan controls, and for firm fixed effects. The results are also robust to not including savings banks (see column (2)) and, only analyze ABSs (see column (3)).

The second stage regression is also highly statistically significant where we regress change in credit volume (columns (1) to (7)) or credit terms (column (8) to (13)) on the predicted variation of securitization by ex-ante real estate exposure. All in all, results indicate that the predicted part of actual securitization by the ex-ante pre-boom real estate assets affects credit supply, both volume and other terms. Moreover, economic significance is similar to Tables III and IV. Finally, the coefficients of ABS are statistically not different than the ones from total securitization (ABS and covered bonds), especially when we have more controls (compare for example column (6) and (7); though statistically not different, the estimated coefficient on drawn to committed for ABS is much higher). This is further consistent with the notion that liquidity provision through the ability to securitize is driving our results, as ABS allows some capital relief whereas covered bonds only provides liquidity, but no capital relief.

#### 3.7 Firm-level Aggregate Lending Channel and Real Effects

In Table III and Figure 1 we already find that there is no firm level effects in credit volume in the boom of 2004-07. In Table IX we also estimate the net firm-level impact of bank lending channel for draw-to-commitment ratio, maturity and collateralization. Columns (1) though (3) show that changes in all three of these outcomes are significant at firm level. Thus,

access to liquidity. Even for a bank that has not yet securitized many of its assets, the knowledge that the bank has securitizable assets can make it to extend new credit (Allen and Gale (2007) and Shin (2009)). Fifth, for our paper is not so crucial the origin of the shock, but the different effects from loan-level vs. firm-level estimations.

while loan level impact in credit quantity is undone by firm-level adjustments, the same is not true for other credit terms and conditions. As banks with real estate exposure become more willing to extend credit, there is greater competition for a given firm's overall debt capacity. The competition results in borrowing firms receiving softer, more favourable credit terms.<sup>18</sup> Moreover, columns (4) through (6) of Table IX show that firms borrowing from banks with greater real estate exposure *do not* experience any differential change in propensity to default, sales or number of employees. Hence, results suggest that despite of large effects at the bank-firm level, the crowding-out completely mitigates these effects for firm real outcomes in good times for firms with established banking relationships.

### 4. Conclusions

Our results are interesting for macroprudential policy and theory. The results suggest that credit supply booms lead to modest positive real effects but to substantial higher bank risk-taking, including softer lending standards and new loans that are significantly more likely to default during the downturn, thus credit expansions add fragility to the financial system. These results are in contrast with the crisis, with a sharp reversal in credit. Our framework also uses credit register data that are available in most countries around the world (see e.g. Djankov, McLiesh and Shleifer (2007)). Our framework is thus practical to implement and should help central banks to gain a better understanding of the overall strength of the bank lending channel in the economy. This is even more important nowadays given the new macroprudential supervision powers for the Federal Reserve and the European Central Bank, and also given the new bank capital and liquidity regulation (Basel III).

<sup>&</sup>lt;sup>18</sup> Note that because firm fixed effects do not significantly change the estimated coefficient of real estate exposure, the bias-corrected estimated coefficient is not different statistically. In addition, all these results are robust to the other tests we have done for the loan-level analysis (Table III and IV). In addition, we do not find significant effects, even for the smaller firms (see Table III of the Online Appendix). In the Online Appendix, we also instrument the credit granted by ex-ante real estate exposure in explaining real effects with similar results.

#### References

Allen, Franklin and Douglas Gale (2007), "Understanding Financial Crises". Clarendon Lecture Series in Finance. Oxford: Oxford University Press.

Adrian, Tobias and Hyun Song Shin (2009), "Money, Liquidity and Monetary Policy", *American Economic Review*, 99(2), 600-5.

Bernanke, Ben (1983), "Non monetary Effects of the Financial Crisis in the Propagation of the Great Depression", *American Economic Review* 73(3): 257-276.

Dell'Ariccia, Giovanni and Robert Marquez (2006), "Lending Booms and Lending Standards", *Journal of Finance* 61(5), 2511-2546.

Diamond, Douglas and Raghuram Rajan (2001), "Liquidity Risk, Liquidity Creation and Financial Fragility: A Theory of Banking", *Journal of Political Economy*, 109(2), 287-327.

Djankov, Simeon, Caralee McLiesh, and Andrei Shleifer (2007), "Private Credit in 129 Countries", *Journal of Financial Economics*, 84(2), 299-329.

Freixas, Xavier, Luc Laeven, and José-Luis Peydró (2015). "Systemic Risk, Crises and Macroprudential Regulation", MIT Press.

Luca Guerrieri & Matteo Iacoviello (2013) "Collateral constraints and macroeconomic asymmetries," working paper 1082, Board of Governors, Federal Reserve System (U.S.).

Iyer, Rajkamal, José-Luis Peydró, Samuel da-Rocha-Lopes, and Antoinette Schoar (2014), "The Interbank Liquidity Crunch and the Firm Credit Crunch: Evidence from the 2007-09 Crisis", *Review of Financial Studies*.

Jiménez, Gabriel, Steven, Ongena, José-Luis Peydró, and Jesús Saurina (2012), "Credit Supply and Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications", *American Economic Review*, 102(5), 2301-26.

Jiménez, Gabriel, Steven, Ongena, José-Luis Peydró, and Jesús Saurina (2014), "Hazardous Times for Monetary Policy: What do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk?", *Econometrica*, 82 (2), 463-505.

Jordà, Oscar, Moritz Schularick, and Alan M. Taylor (2013), "When Credit Bites Back," *Journal of Money, Credit and Banking* 45(S2): 3–28.

Khwaja, Asim I. and Atif Mian (2008), "Tracing the Impact of Bank Liquidity Shocks", *American Economic Review*, September 2008, vol. 98(4), 1413-42.

Maddaloni, Angela and José-Luis Peydró (2011), "Bank Risk-Taking, Securitization, Supervision, and Low Interest Rates: Evidence from the Euro Area and U.S. Lending Standards", *Review of Financial Studies*, 24, 2121-65.

Paravisini, Daniel (2008), "Local Bank Financial Constraints and Firm Access to External Finance", *Journal of Finance* 63(5), 2161-93.

Peek, Joe and Eric S. Rosengren (2000), "Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States", *American Economic Review*, 90(1): 30-45.

Shin, Hyun (2009), "Securitization and Financial Stability", Economic Journal, 309-332.

Schnabl, Philipp (2012), "The International Transmission of Bank Liquidity Shocks: Evidence from an Emerging Market", *Journal of Finance* 67(3), June, 897-932.

Schularick, Moritz, and Alan M. Taylor (2012), Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008. *American Economic Review* 102(2): 1029–61.