House Prices and Misallocation: The Impact of the Collateral Channel on Productivity*

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Abstract

This paper empirically investigates the impact of local house price booms on capital misallocation within manufacturing industries. Using the geographical variation provided by the salient Spanish housing boom (2003-2007), we show that manufacturing firms exposed to positive local house price shocks received more credit from banks and their investment grew more intensively when they had a larger proportion of collateralizable real estate assets. We exploit the geographical variation in both house prices and pre-boom urban land supply at the municipality level to document that this collateral channel was exacerbated for firms located in urban land-constrained areas where real estate appreciation was larger. The interaction of geographical conditions, that led to heterogeneous housing booms, with the collateral channel on investment resulted in an increasing dispersion of the capital-labor ratio within industries. A simple counterfactual calculation suggests that the capital misallocation generated by the collateral channel on investment could account for around 40% of the fall in TFP experienced by the Spanish economy during the housing boom.

Keywords: Housing Boom, Misallocation, Collateral Channel, Productivity.

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1 Introduction

Productivity growth started to decline before the onset of the global financial crisis of the late 2000s in several advanced economies (Fabina and Wright, 2013, Fernald, 2015). This slowdown in productivity occurred during a period of economic expansion sustained by strong internal demand that coincided with large increases in house prices and corporate debt in some advanced economies, such as the United States or many European countries. The coincidence of these remarkable macroeconomic facts underlines the need for a better understanding of the relationship between house price booms and the dynamics of corporate investment and productivity. In this paper, we exploit the salient case of the Spanish housing boom (2003-2007) to empirically investigate the potential causal effect of house price fluctuations on corporate investment and credit through the impact of local house price shocks on the collateral value of firms. Through the identification of this channel, we examine the capacity of heterogeneous local housing booms to generate capital misallocation within industries, and thereby create aggregate productivity losses in the economy.

Spain is a proper case to analyze the link between house prices, credit-funded investment and productivity dynamics.[1] In fact, an outstanding housing boom coincided with a significant growth in corporate investment, which registered a cumulative increase of 70% between 2000 and 2007. The remarkable accumulation of capital by the corporate sector was mainly financed through credit from the banking sector, resulting in the surge of the debt of non-financial institutions from 64% to 124% of GDP during this period. The expansion of corporate credit was spread throughout the major sectors of activity and was fueled by loans secured by real estate assets, in a context in which house prices increased at a cumulative rate of 120% from 2000 to 2007 (IMF, 2011, Santos, 2014, Jiménez et al., 2020). As a result of these events, real GDP expanded at an average annual growth rate of 3.5% but, as documented in Garcia-Santana et al. (2020), this growth was driven by factor accumulation, while total factor productivity (TFP) declined. The fall in real productivity in the Spanish economy during this period represented an average annual rate of -0.4 according to the estimates by Feenstra, Inklaar and Timmer (2015) or those provided by EUKLEMS (Stehrer et al., 2019).[2]

To rationalize the connection between these aggregate developments, we consider a stylized static partial equilibrium model in which firms with an heterogeneous composition of collateralizable assets face borrowing constraints. The model isolates potential interactions between house prices and firms' composition of assets that can lead to heterogeneous borrowing capacity

[1] See Section 2 for a more detailed discussion of the house price, investment, and corporate debt dynamics that occurred in Spain during this period, as well as descriptive evidence comparing these events with those observed in the United States and in the main economies of the euro area.

[2] The evidence on the dynamics of productivity by sectors of activity reveals that its fall in Spain during this period cannot be explained exclusively by an increase in the relative weight of the construction and real estate sectors in the economy (IMF, 2011). This evidence also indicates that less than half of Spain's productivity gap with the rest of the euro area can be attributed to differences in the sectoral composition of activity.

and investment rates among firms within an industry. The predictions of the model guide our empirical analysis and rely on two fundamental assumptions. First, in line with the collateral channel literature (e.g., Chaney, Sraer and Thesmar, 2012), we postulate that the borrowing capacity of firms depends on the valuation of their real estate assets. Second, consistent with the urban economics literature (Glaeser, Gyourko and Saiz, 2008, Saiz, 2010), we assume that initial local geographical conditions determine housing supply and, thus, the response of local house prices during a housing boom. Given these assumptions, the model predicts that during a housing boom firms in municipalities that experience higher house appreciations (due to lower urban land availability) are able to borrow and invest more than firms in the same industry with the same composition of assets but located in areas with lower geographical constraints. At the same time, for firms located in the same geographical area, the model predicts that the effect of a local housing boom on borrowing and investment is exacerbated among firms whose collateral is relatively abundant in real-estate assets. These predictions on the heterogeneous response of firm's investment to local housing booms point to the capacity of these booms to create misallocation of resources within an industry. In line with models *à la* Hsieh and Klenow (2009), this misallocation is defined in our framework as an increase in the industry variance of the capital-labor ratio with respect to the efficient case in which the relative value of firm's assets does not change. The size of this measure of capital misallocation depends on the heterogeneity of local house price booms, whose relative size amplifies the distortion in investment and credit allocation among firms within an industry. Lastly, in the model, this measure of misallocation has a direct relationship to productivity in a given industry, so this collateral channel leads to aggregate productivity losses during a housing boom.

We test the predictions of the model using a panel of manufacturing firms during the Spanish housing boom (2003-2007), which contains detailed information on firms' financial statements and their banking credit. We combine this firm-level database with measures of local house prices and proxies of housing supply elasticities for Spanish municipalities. Taking into account our data availability and the theoretical predictions, we specify an empirical model that considers the potential impact on capital accumulation of the interaction between the relative composition of firms' collateralizable assets and the geographic location of these assets. In a reduced-form investment equation, we proxy the relative weight of real estate assets in the total assets of firms by firms' tangibility rate, meanwhile the impact of geographic conditions on real estate value is captured by local house price shocks. The coefficient associated with the interaction of these two variables measures the differential effect of house prices growth on the investment rate of firms depending on the tangibility of their collateral. The model predicts a positive sign of this coefficient, which implies that an increase in local house prices in a municipality raises the investment rate for the average firm in the sample, and the larger the tangibility of firms' assets, the higher the investment rate. This specification also allows us to estimate the house price elasticity of investment and compute it for different moments of the firm's tangibility rate distribution.

The OLS estimates of our investment equation could be biased because local house prices shocks can be positively correlated with firms' investment opportunities, and these house prices could capture local demand shocks. To address the potential endogeneity of local house prices, we run a two-stage least square (2SLS) estimate of the investment equation where local house price shocks are instrumented using a proxy for the housing supply elasticity in a municipality interacted with the long-term aggregate real interest rate of mortgage loans granted to households by the banking sector. This empirical strategy has been broadly used in the literature that estimates the real effects of house price shocks, and it relies on the assumption that, when a housing boom occurs, local geographic conditions determine the size of the change in house prices at local level, but this change is exogenous to the investment decisions of firms during the boom. For a first empirical assessment of our identification strategy, we provide evidence on several first-stage regressions that indicate the relevance of our instrument and its predictive power on house prices at the municipality level. This identification strategy is also enhanced by the inclusion of a set of industry-location-time fixed-effects that abstract from location-specific shocks that could affect all firms within an industry during a given year.

The OLS and 2SLS estimates of the investment equation are consistent with the main prediction of the model. These estimates indicate not only that the investment rate of the average firm increases when local house prices rise, but also that the larger the tangibility of the firm's assets, the greater the increase in investment. The OLS estimates of both the interaction coefficient and the house price elasticities of investment are lower than those of the 2SLS, consistent with the expected downward bias in the OLS coefficients. The 2SLS estimates of our preferred specification show a house price elasticity of investment for the average firm of 0.13, in a context of a housing boom in which the average local house price increases by 14% annually.[3] These results can be interpreted as a first evidence of capital misallocation through the lens of our model. This misallocation is inferred from estimates that show a heterogeneous causal impact of local house price shocks on capital accumulation that depends on the relative asset composition of firms. For instance, given the same local house price shock, manufacturing firms in the 75th percentile of the tangibility rate distribution invest 98 pp more than manufacturing firms in the bottom 25th percentile. At the same time, the elasticity of investment to changes in house prices is close to 0 for manufacturing firms with the median tangibility rate. This result points out that firms with relatively low tangibility rates could be forced to cut investment during housing booms in the presence of the collateral channel.

Following the predictions of the model, we also specify a reduced-form credit equation to examine the relationship between firms' borrowing capacity and the value of their collateral. The OLS and 2SLS estimates of this equation are consistent with theoretical predictions and

[3] To put this result in the context of the literature, these estimates can be compared to the main estimate in Chaney, Sraer and Thesmar (2012) that situates the house price-investment elasticity at 6% for the average firm in the U.S.

indicate that firms within an industry located in municipalities experiencing higher house price appreciations receive more bank credit (intensive margin), and the allocation of this credit is positively related to the tangibility of their collateral. The 2SLS estimates show a remarkable magnitude of this impact with a sizeable house price elasticity of credit for the average manufacturing firm of 0.29. These estimates also show a heterogeneous impact of local house prices on corporate credit such that the larger the share of firms' tangible fixed assets, the larger the additional credit growth for the same local house price shock. As a complementary result, we report estimates of several discrete choice models that show the relevance of the collateral channel in the extensive margin of credit. Specifically, the estimates indicate that local house price shocks increased the number and proportion of new bank loans for firms that had a larger proportion of collateralizable real estate assets.

Finally, we undertake several sensitivity analysis to evaluate the robustness of our findings. First, we explore the possible heterogeneous impact of the collateral channel depending on the size of the firm or the type of bank (commercial or savings bank) that provided credit to firms. The estimates presented show that neither firms of a specific size nor the type of the main credit provider drive our baseline results, ruling out the possibility that the average impact of the collateral channel during the housing boom was due to a particular segment of the demand or supply of capital. Second, we control for time-varying firm variables (which are not constant at the industry-region-year level) that can be confounding factors of both investment and credit, and could also be related to both the valuation of corporate collateral and our instrument for local house price shocks. This analysis shows that our results are robust to the inclusion of two covariates that control for firms' financial conditions (the leverage ratio and financial costs), as well as to the inclusion of firms' productivity shocks that control for the supply determinants of capital accumulation. Third, in our baseline regressions we add predictors of the firms' tangibility rate (quintiles of the firms' initial log asset value) interacted with the log change in house prices, in order to mitigate the potential source of bias created by the endogeneity of the tangibility decision over time. The inclusion of these predictors of the firms' tangibility rate produces minor changes in the house prices elasticities of investment and credit. Lastly, we perform additional robustness tests on our main estimates to explore the sensitivity of our results to alternative definitions of the investment rate; the impact of excluding from the estimation sample firms that are subsidiaries of multinational firms and large firms located in small or medium-sized municipalities; the effect on efficiency of our estimates of clustering standard errors at different levels; the relevance of the collateral channel beyond manufacturing industries; or the robustness of our results using alternative measures of real estate collateral. This set of sensitivity analysis supports the empirical relevance of the firms' collateral channel in both investment and bank credit allocation within industries.

In the last section, we explore the quantitative contribution of the capital misallocation generated by the collateral channel on investment to explain the fall of aggregate productivity in the Spanish economy between 2003 and 2007. To examine the potential aggregate effects of the collateral channel, we first undertake a growth accounting exercise guided by our model to quantify the decline in aggregate TFP in response to an increase in the variance of the capital-labor ratio that is uniquely driven by a housing boom. This exercise illustrates the capacity of the collateral channel on investment during a housing boom to generate a capital deepening process that drives economic growth despite resulting in declining TFP. In a complementary back-of-the-envelope exercise, we perform a simple counterfactual quantification of the actual impact of the housing boom on aggregate productivity through its effect on the dispersion of capital within industries. In this exercise, we first compute the positive correlation between local house price shocks and the dispersion across the geographical space of the log of the capital-labor ratio within industries. The obtained estimates are consistent with the theoretical prediction that the average dispersion of capital in a given industry increased more in municipalities that experienced a larger increase in house prices, revealing a misallocation of resources. The second required component in our quantification is a measure of the aggregate house price distortion caused by the housing boom. To obtain this measure, we follow Glaeser, Gyourko and Saiz (2008) and Mian and Sufi (2011) and make the conservative assumption that the average size of the house price shock in the economy can be proxied by the differential average growth rate in the mean price of houses located in the first and the fourth quartile of the pre-boom buildable urban land ratio distribution of the municipalities in Spain. Using our estimates of the price elasticity of the variance of the capital-labor ratio and the actual log difference in real house price growth, we calculate that the housing boom could account for between 28.5% and 41.5% of the increase in the dispersion of capital within industries in the market economy between 2003 and 2007. Considering our preferred specification and the one-to-one theoretical mapping between changes in the variance of the log capital-labor ratio and changes in TFP, this back-of-the-envelope computation indicates that the differential growth of local house prices (created by the housing boom) can account for around 40% of the decline in aggregate productivity in the Spanish market economy during the 2003-2007 period.

Related literature. This paper relates to different strands of the literature. First, the paper is related to the literature on firms' misallocation of resources that originates from the seminal paper by Hsieh and Klenow (2009). Since then, there has been a large number of empirical investigations on the reasons why the actual allocation of inputs may depart from the optimal one (see Jones, 2016). Among them, this paper is related to research that investigates the role of financial frictions and housing booms in creating misallocation of resources. In this branch of studies, Midrigan and Xu (2014) and Banerjee and Duflo (2014) show the capacity of financial frictions to reduce aggregate productivity and, therefore, the possible improvement in the allocation of inputs among firms when loosening financial restrictions. We differ from these contributions by documenting an increase in misallocation within industries when there is an easing of financial conditions biased towards a specific type of asset, such as real estate assets during a housing boom. This bias implies that the relative price of assets is distorted thereby creating a distortion in the allocation of capital within industries towards firms relatively more endowed with the higher priced assets, thus reducing aggregate productivity. On the role of housing booms to create misallocation, the literature has focused more on the sectoral distortions created when booms transfer resources to construction and real estate activities, draining inputs from other productive activities such as manufacturing (Basco, 2016; Garcia-Santana et al., 2020)[4]. Instead, this paper examines the capacity of local housing booms to spread their effects and create capital misallocation and lower TFP in industries not directly related with construction or real estate sectors.

The paper is also related to the literature that connects housing booms with corporate investment and the allocation of credit across firms. One strand of this literature focuses on the financial transmission of the housing boom to non-housing sectors due to the existence of financial frictions in the banking system. Chakraborty, Goldstein and MacKinlay (2018) show that rising house prices during the housing boom in the U.S. (1998-2006) resulted in a crowding out effect in the credit market as financially constrained banks decreased commercial credit. Banks that were active in strong housing markets looked for higher returns by allocating more credit to housing-related activities (e.g., mortgage lending) at the expense of corporate lending. Martín, Moral-Benito and Schmitz (2021) also find this crowding-out effect of corporate credit in Spain during the first years of the 2000s. However, they show how this effect is reversed during the peak of the housing boom when financially constrained banks that were more exposed to real estate increased their net worth, expanded their supply of credit, and triggered a crowding-in effect that increased credit for the average firm[5]. In this paper we focus on an alternative mechanism that relates housing booms to changes in corporate credit: the collateral channel of firms. We show that through this channel firms in industries non-related to housing activities but more exposed to local house price booms received more credit. In this sense, the paper is related with several papers that have studied the connection between house price fluctuations and corporate investment[6]. In particular, our mechanism is close to Chaney, Sraer and Thesmar (2012) that showed the existence of a sizeable collateral channel on the U.S. corporate investment. However, we complement these previous results pointing out how the interaction between the collateral channel and local housing booms can be a source of misallocation of resources within industries. This misallocation emerges because firms relatively more endowed with real estate assets exposed to larger local house price shocks accumulate more capital than otherwise identical firms in the same industry. This mechanism also differentiates our contribu-

[4]The literature has examined the impact of housing booms on the sectoral composition of activity. For instance, Arce, Campa and Gavilán (2013) provide a model to explain how differences in the composition of collateral across sectors can explain the relative increase in investment and debt in the construction sector relative to the manufacturing sector during a credit boom driven by a fall in interest rates.

[5]An additional supply mechanism that would have stimulated credit growth during the Spanish housing boom is explored in Jiménez et al. (2020). This paper examines the role of mortgage securitization as a channel that provided additional liquidity to the Spanish banks most exposed to the real estate sector to expand the credit supply.

[6]The literature has also examined the effect of the collateral channel on employment dynamics. For instance, Adelino, Schoar and Severino (2015) show the relevance of this mechanism in explaining higher employment growth for small business during the house price boom in the U.S. between 2002 and 2007.

tion from a closed paper to us by Gopinath et al. (2017). In the latter, the authors argue that a declining trend in real interest rates pushed capital inflows in southern euro-area economies causing a misallocation of capital towards firms with more net worth and thereby reducing the TFP in countries like Spain. Instead, we identify a micro-mechanism associated to local house prices that can explain how capital inflows, when associated with housing booms, can create misallocation of capital within manufacturing industries. The consideration of heterogeneous local house prices booms introduces a geographical dimension in the misallocation of inputs that allows us to explore the quantitative contribution of housing booms to create aggregate productivity losses in the economy.

This paper is also related to the urban economics literature that shows the impact of initial geographical conditions on the evolution of local house prices (Glaeser, Gyourko and Saiz, 2008, Saiz, 2010), as well as the investigations that relate this connection to the evolution of credit and the real economy (Mian and Sufi, 2009, Mian and Sufi, 2011, and Mian, Rao and Sufi, 2013). We contribute to this literature by considering the relationship between geographical conditions, through their impact on local house prices, and the misallocation of capital within industries. The geographic dimension of misallocation is also explored in Hsieh and Moretti (2019) that showed the significant impact of local restrictions on housing supply to create spatial misallocation of labor across metropolitan areas in the United States. We also explore this spatial channel, but instead identify the impact of housing supply constraints on capital misallocation within industries as a source of aggregate productivity losses.

The paper proceeds as follows. In section 2, we present suggestive aggregate evidence on the remarkable dynamics of credit-funded corporate investment, house prices and productivity occurred in Spain during the late 2000s. In section 3, we lay out a stylized model that connects the collateral channel of investment and credit created by local house price booms with capital misallocation within manufacturing industries. Section 4 introduces the administrative firm-level and municipality-level data used in our empirical analysis. In section 5, we first present the identification strategy to estimate the causal impact of local house price booms in investment and credit across manufacturing firms. Then, we discuss the estimates obtained from an instrumental variable procedure and the implications of these results in terms of capital misallocation. In section 6, we provide a back-of-the envelope computation on the aggregate effects of local house price booms on productivity through the misallocation of capital among manufacturing industries. Section 7 concludes.

2 Macroeconomic Background and Suggestive Evidence

In this section, we document the salient macroeconomic event that occurred in Spain in the late 2000s. We argue that this episode was exceptional in terms of house prices, investment, and corporate debt dynamics, and we relate these developments to productivity dynamics as well as to local real estate market conditions prior to the housing boom. We interpret this relationship as suggestive evidence of the connection between housing booms and aggregate productivity through the collateral channel.

The boom in house prices in Spain in the late 2000s was a major macroeconomic event by international standards. Indeed, Figure 1a shows the evolution of the Case-Shiller residential house price indices in Spain and in the United States (U.S.). Note that the extraordinary housing boom in the U.S. resulted in a cumulative house price growth of 70% between 2000 and 2007, meanwhile in Spain house prices rose by more than 120% during the same period. This impressive increase in house prices in Spain was heterogeneous across municipalities and correlated with local geographical conditions. To give empirical content to these geographical conditions, we use the ratio of buildable urban land at the municipality in 1997 (before the housing boom). This measure was built in Basco, Lopez-Rodriguez and Elias (2022) in the spirit of the measure of housing supply elasticity developed by Saiz (2010) for the U.S.[7] Simple descriptive evidence indicates that the average (real) house price growth per square meter during the peak of the housing boom (2003-2007) was 9.5 percentage points higher for municipalities in the bottom quartile of the land availability distribution than in the top quartile. For ease of exposition, we label the municipalities in these percentiles as housing supply inelastic and elastic municipalities, respectively.

The large increase in house prices coincided with a boom in non-residential corporate investment in Spain. The magnitude of this boom was not comparable with the dynamics of investment in other developed countries. As illustrated in Figure 1b, the non-residential corporate investment in Spain grew by 70% between 2000 and 2007. In contrast, other large economies in the euro area with a common monetary policy, such as Italy or Germany, experienced cumulative increases of just 26% and 35%, respectively. The U.S. also experienced a slower growth path than Spain with a cumulative increase of 33% in non-residential corporate investment during the expansion that started in 2002 (OECD, 2018). In addition to the aggregate figures, the non-residential investment boom in Spain was also heterogeneous across municipalities and the size of this boom was also correlated with local housing market conditions before the boom. This geographical heterogeneity can be seen in the descriptive statistics on the percentage change in the average real stock of capital per labor expenditures of firms located in elastic and inelastic municipalities over time.[8] For instance, the average real stock of capital per labor expenditures between 2000 and 2007 increased by 180% in housing supply inelastic municipalities, whereas it only increased by 35% in the municipalities with an elastic housing supply. In contrast, the drop in the real stock of capital per labor expenditure in 2013, from the peak of the boom in 2007, was larger in inelastic municipalities (-35% versus -8%) that also experienced a larger fall in house prices than elastic ones. This evidence hints to a

[7] See subsection 4.2 for details on the measures used for buildable urban land and residential house prices.

[8] The average real stock of capital per labor expenditure in each municipality-quartile is obtained by weighting the capital-labor ratio of each firm by the firm's share in the aggregate production of that quartile of the distribution of municipalities.

connection between local house price dynamics and investment related to local housing market conditions prior to the boom.

Spanish non-financial corporations funded their investment projects with intensive use of banking credit. As a result of this trend, the aggregate corporate leverage ratio in terms of GDP increased in Spain well above the rise in this ratio in other euro area economies that also received capital inflows during the 2000s (see Figure 1c). One outstanding feature of banking credit in Spain during this period was the growing relevance of loans collateralized with real estate assets (see Figure 1d). As an example, the ratio of credit to non-financial corporations that had real estate assets as collateral reached 45% of the total credit granted in 2007, which represented 35% of GDP. Note that the peak in collateralized credit also coincides with the peak in house prices (see Figure 1a).

The use of collateralized loans was particularly relevant in the manufacturing sector. According to the Central Credit Register of the Bank of Spain, the share of credit granted in commercial and industrial loans backed by real guarantees was, on average, 82% between 2000 and 2007. The remarkable increase of house prices in Spain emerges as a potential explanation for the boom in collateralized loans that fueled private investment through banking credit. Arguably, this mechanism could have been more powerful in areas where geographical conditions limited the housing supply and, thus, house prices increased more.

The Spanish boom in non-residential corporate investment financed by debt coincided with an increase in standard empirical measures of capital misallocation within industries (Gopinath et al., 2017). Figure 2 provides suggestive evidence on the potential contribution of local housing markets conditions to exacerbate this misallocation of capital. The figure shows the evolution of an average measure of capital misallocation for firms located in elastic and inelastic municipalities, and for the average municipality between 2000 and 2012. We measure misallocation using the variance of the log capital-labor ratio in real terms, which is considered a key determinant of productivity dynamics (Hsieh and Klenow, 2009). The variance of the real capital-labor ratio in the average municipality increased by 27.3% between 2000 and 2007, which points to a rising aggregate misallocation of capital in Spain. This aggregate fact was also documented in Gopinath et al. (2017). However, this aggregate figure masks the geographical heterogeneity that is reflected in the differential increase across municipalities depending on their (pre-boom) urban land availability. Note that the lines for elastic and inelastic housing supply municipalities grow apart during the housing boom and start to converge after the burst. Quantitatively, during the 2000-2007 period, the increase in the variance of the log real capital-labor ratio in the inelastic municipalities (40.1%) almost doubled the increase in the elastic ones (23.5%).

3 House Prices, Investment and Misallocation

This section presents a simple theoretical model to derive empirical predictions on the effects of local house price booms on corporate investment and banking credit when firms exhibit a heterogeneous composition of collateralizable assets. The model also serves the purpose to define the concepts of capital misallocation and local housing booms used in this paper. These definitions are necessary to derive the conditions under which the misallocation of capital within industries, caused by a collateral channel, can create productivity losses in the economy.

To isolate the impact of a collateral channel on corporate investment, we consider a stylized static partial equilibrium model in which firms with an heterogeneous composition of assets face borrowing constraints. We assume an economy composed of J industries but, for simplicity, we consider one representative industry. In this industry there is a continuum of firms with mass I, indexed by i. Firms are endowed with physical capital k, measured in terms of capital per worker[9], used for production and two non-productive capital inputs that can be collateralized: real estate assets h_i and non-real estate assets η_i.

We assume that financial markets are not perfect. Borrowers could avoid total repayment of debt by paying a fraction θ of the value of their collateralized assets. Thus, firms face the following borrowing constraint, $Rd_i \leq \theta \left[ps_i^h H + \eta_i\right]$, where R is the real interest rate, d_i, is the amount borrowed by firm i, p is the price of real estate assets and $s_i^h = h_i/H$ is the share of real-estate assets owned by firm i and H is the total stock of real estate assets in the municipality.[10] All firms have access to the same production technology, $f(k) = Ak^{\alpha}$, where $A = 1$ for all firms. We assume that $f'(k) > R$, which guarantees that the borrowing constraint is binding. Market clearing implies that $k = d$, thus, the investment (and credit) of firm i is $k_i = d_i = \theta \left[ps_i^h H + \eta_i\right]/R$.

In this economy, goods and capital markets are integrated but real estate markets are local. We assume that there is a continuum of municipalities with mass M, indexed by m. The real estate assets of each firm are located in a municipality m where the firm is placed. We assume that in each municipality the supply of housing is given by $H_m^S = h_m(p_m, \varepsilon_m) = p_m^{\varepsilon_m}$, where p_m is the house price and ε_m is the elasticity of the housing supply in municipality m. We denote by $\sigma_m = \sigma$ the fundamental demand for houses in the municipality.

To isolate the effect of the heterogeneous composition of collateralized assets on firms' investment and input allocation, we assumed above that firms have the same technology and

[9]The model focuses on the allocation of capital assuming that labor is perfectly elastic. Therefore, for simplicity, we normalize aggregate labor L to 1.

[10]The micro-foundation of this borrowing constraint is the presence of moral hazard in the lender-borrower relationship. As in the seminal paper by Kiyotaki and Moore (1997), the borrower needs to provide assets as a collateral to obtain credit. The parameter θ could be interpreted as a measure of financial development, so that the lower is θ, the less costly is to avoid repayment and, therefore, the less credit will be granted. Monacelli (2009) and Basco (2014) use a similar collateral constraint.

idiosyncratic productivity and, thus, the only difference between firms within an industry is their composition of assets. For simplicity, we assume that *low indexed-i* firms only own real estate assets and *high indexed-i* firms uniquely own non-real estate assets.[11] The distribution of real and non-real estate assets among firms is, therefore, given by:

$$s_i^h = \begin{cases} \frac{1}{\kappa} \text{ if } i < \kappa \\ 0 \text{ if } i > \kappa \end{cases}$$

$$\eta_i = \begin{cases} 0 \text{ if } i < \kappa \\ \eta \text{ if } i > \kappa \end{cases}$$

In line with the suggestive macroeconomic evidence for Spain described in section 2, we assume that a housing boom emerges in this economy and this boom is heterogeneous across municipalities as a result of different initial geographical conditions. To parametrize the housing boom, we assume that the housing (real estate) demand in municipality m is given by $\sigma + B$, where $B > 0$ is the decoupling from fundamental demand. We assume, for analytical simplicity, that this decoupling, B, is homogeneous across municipalities. These assumptions imply that, given the housing supply in the municipality, the equilibrium house price is $p_m^* = (\sigma + B)^{1/\varepsilon_m}$, which is directly related to the decoupling of housing demand, B, and inversely related to the elasticity of housing supply in the municipality, ε_m. The increase in house prices created by a decoupling of demand is what we label as a housing boom. Note that, given a level of decoupling of demand B, the local housing boom is larger in municipalities with a lower housing supply elasticity (see Glaeser, Gyourko and Saiz (2008), Mian and Sufi (2011) or Basco (2014) for a theoretical justification and evidence for the U.S.). Thus, lower housing supply elasticities create larger increases in local house prices when the wedge between local housing demand and its fundamental level widens.[12]

We last assume a symmetry condition such that $\eta = \frac{1}{\kappa}\sigma^{\frac{1+\varepsilon}{\varepsilon}}$. This assumption implies that, in the absence of local housing booms, the price of real and non-real estate assets is the same and, therefore, the value of the endowment is homogeneous across firms.

[11] This assumption simplifies the notation and algebra, but it is important to note that the predictions of the model are the same when assuming that firms have both types of collateralizable assets but in different proportions. This simplifying assumption implies that the theoretical derivations in this section provide predictions in terms of averages.

[12] We make these assumptions to consider the case in which the housing demand is above its fundamental level, in line with the real estate market in Spain over the period 2003-2007 that preceded the house price burst (Santos, 2014). However, in the model, we do not take a stand on the origin of the demand decoupling or on the roots of the so-called housing bubble in Spain. Therefore, this framework is consistent with several alternative explanations of the origin of the housing boom, such as i) a potential rational housing bubble due to a shortage of assets created by international capital inflows (see Basco, 2014 for a theoretical model on this mechanism); ii) the existence of unrealistic expectations about future house price increases (see Case and Shiller, 2003 for a discussion of this channel in the United States); iii) the presence of behavioural housing bubbles that explain capital inflows (Laibson and Mollerstrom, 2009); or iv) the emergence of rational housing bubbles rising from financial frictions in a closed economy (Arce and López-Salido, 2011).

Considering these assumptions, we derive a set of empirical predictions on the effects of local housing booms on corporate investment, credit and allocation of capital within an industry when firms have a heterogeneous composition of collateralizable assets and they are placed in different geographical locations.

Prediction 1 *In an economy (municipality) that experiences a housing boom, the investment rate (and the allocation of credit) increases relatively more among firms within an industry that own real estate assets. Given the composition of collateralizable assets, the difference in relative investment rates (and credit growth) among firms within an industry is larger for firms located in municipalities with lower housing supply elasticities, which experience larger house price increases.*

The equilibrium relative investment rate of firms that own real estate assets ($i < \kappa$) located in municipality m that experiences a housing boom (B), with respect to an equilibrium rate without a housing boom (NB), is[13]

$$\frac{k_m^{\text{with real estate, B}}}{k_m^{\text{without real estate, B}}} = \frac{\frac{1}{\kappa}\left[\sigma + B\right]^{\frac{1+\varepsilon_m}{\varepsilon_m}}}{\eta} \equiv \Phi(B, \varepsilon_m) > 1 = \frac{k_m^{\text{with real estate, NB}}}{k_m^{\text{without real estate, NB}}}.$$

This expression implies that for the set of firms within an industry located in the same municipality, the relative investment rate of firms that own real estate assets (with respect to firms without those assets) increases when there is a housing boom in the municipality ($B > 0$). Note that, in the absence of a housing boom ($B = 0$), all firms invest the same amount since the value of their assets is homogeneous and we assumed the same production technology among firms. Given the market clearing condition, $k = d$, the same expression and interpretation applies to credit growth.

We obtain a similar expression that illustrates the amplifying effect on investment rate (credit growth) differentials among firms in the same industry located in different municipalities. In particular, given the same composition of collateralizable assets and the same decoupling of housing demand, B, the difference in relative investment rates (credit growth) among firms within an industry is larger for firms located in municipalities with a more inelastic housing supply:[14]

$$\Phi(B, \varepsilon_m) > \Phi(B, \varepsilon_{m'}) \text{ if } \varepsilon_m < \varepsilon_{m'}.$$

The intuition for this result is that a housing boom increases the collateral value of firms that

[13]Note that we are using the equilibrium house price to obtain this expression. In particular, in each municipality m, the relative investment rate is given by $k^w/k^{nw} = (1/\kappa)(p^* \cdot \mathrm{h})/\eta$, where $p^* = (\sigma + B)^{1/\varepsilon}$ and $h = p^\varepsilon$. The superscripts w and nw denote, respectively, with and without real estate assets.

[14]It is straightforward, given the symmetry condition, to show that $\Phi(B, \varepsilon) > 1$. In addition, $\frac{\partial \Phi(B,\varepsilon)}{\partial \varepsilon} < 0$ because $\frac{1+\varepsilon}{\varepsilon}$ decreases with ε.

own real estate assets. This effect is exacerbated in municipalities where ε is small because the increase in housing prices decreases with the housing supply elasticity. This channel indicates that the accumulation of capital across space is shaped by geographical conditions. Note that in the absence of a housing boom, i.e., when housing demand is equal to its fundamental level, firms with different assets composition have the same endowment value and therefore invest the same amount regardless of their geographic location.

In case we considered the existence of credit rationing in this economy, a corollary would be that the likelihood of receiving credit depends on the value of the firms' collateral. In the presence of local housing booms, within an industry, firms are more likely to receive credit when they own real estate assets. The larger the size of the local housing boom, i.e., the lower the housing supply elasticity, the larger the probability of receiving credit when firms own real estate assets.

Prediction 2 *In an economy (municipality) that experiences a housing boom, the dispersion of capital among firms within an industry is larger when firms have heterogeneous valuations of their collateralizable assets. This misallocation of capital within an industry is larger when municipalities experience heterogeneous appreciations of house prices due to their initial geographical conditions (i.e., heterogeneous housing supply elasticities).*

This result follows directly from the investment prediction. Given the equilibrium investment for firms within an industry, the standard deviation of capital in municipality m that experiences a housing boom (B), with respect to the equilibrium in which the municipality does not experience a housing boom (NB), is given by

$$st.d(k)_m^{\mathrm{B}} = (\Phi_m - 1)\frac{[(M-\kappa)M\kappa]^{\frac{1}{2}}}{\Phi_m \kappa + M - \kappa} > 0 = st.d(k)_m^{\mathrm{NB}}. \tag{1}$$

This expression indicates that in the benchmark case in which no municipality experiences a housing boom, $\Phi_m = 1$ for all m, the standard deviation of capital within an industry is zero. In this case, the heterogeneity in the composition of collateralizable assets across firms does not create misallocation of capital. In the case of a local housing boom occurring, $\Phi_m > 1$ for some m, the standard deviation of capital among firms within an industry is positive when firms located in this booming municipality do not have the same composition of assets (i.e., it would be greater than zero unless all firms had real estate assets ($\kappa = M$), or no firm had real estate assets ($\kappa = 0$)).

In the case that municipalities experience heterogeneous local housing booms, the dispersion of capital within an industry increases when firms have a heterogeneous valuation of their collateral. In fact, even when firms have the same composition of collateralizable assets, the dispersion of capital within an industry increases when firms are located in municipalities with different elasticities of housing supply. That is, $st.d(k)_m^{\mathrm{B}} > st.d(k)_{m'}^{\mathrm{B}}$ if $\varepsilon_m < \varepsilon_{m'}$. This is the case because $\frac{\partial st.d(k)^B}{\partial \varepsilon} < 0$, given $\frac{\partial \Phi}{\partial \varepsilon} < 0$.

This prediction implies that the capital allocation within an industry is less efficient when a housing boom gives rise to heterogeneous local house price booms across municipalities. The intuition is that firms located in areas where house prices are booming can invest more and obtain more credit just because the value of their real estate assets increases more than the collateral value of firms located in municipalities that experience lower house price appreciations. Thus, geography emerges as a channel that shapes the allocation of capital through its impact on real estate prices. The following prediction relates this misallocation of capital to lower TFP.

Prediction 3 *The average TFP within an industry is lower when a housing boom creates a change in the relative valuation of firms' collateralizable assets. Given a heterogeneous composition of collateralizable assets across firms within an industry, the decline in the (average) industry TFP is larger when a higher proportion of firms are located in municipalities with lower housing supply elasticities, which experience higher house price appreciations.*

We compute a measure of the average TFP within an industry departing from the common production function $f(k) = k^{\alpha}$. Given the simplifying assumption on two types of firms in terms of the composition of collateralizable assets, the aggregate output in an industry is $Y = [k_1^{\alpha}]^{\frac{\kappa}{M}} [k_2^{\alpha}]^{\frac{M-\kappa}{M}}$, where 1 refers to firms with low-i index, and 2 to firms with high-i index. Considering that $Y = TFP \cdot \mathrm{K}^{\alpha}$, it follows that the average TFP within an industry when the size of the housing boom is the same in all municipalities ($\Phi_m = \Phi$) is given by

$$TFP = \left[\frac{\Phi\kappa}{\Phi\kappa + M - \kappa}\right]^{\alpha\frac{\kappa}{M}} \left(\frac{M-\kappa}{\Phi\kappa + M - \kappa}\right)^{\alpha\frac{M-\kappa}{M}}. \tag{2}$$

It is straightforward to see from equation 2 that industry TFP has an inverse-U shape with a maximum at $\Phi = 1$, in the absence of a housing boom (NB) when the demand of housing equals the fundamental level in all the municipalities ($TFP^{max} = TFP^{NB}$). In this case, all firms invest the same, which is the efficient allocation that maximizes TFP given that firms have the same technology. When municipalities experience the same local housing boom ($B > 0$), the collateral value of firms that own a higher proportion of real estate assets increases relatively more ($\Phi > 1$) and, therefore, the average TFP decreases ($TFP^{B} < TFP^{NB}$) because firms with a larger share of real estate assets accumulate more capital. In the case that municipalities experience heterogeneous local housing booms, Φ would differ across municipalities. Then, equation 2 would result in a weighted average of industry TFP contributions at the municipality level, weighting each contribution by the mass of firms located in each municipality. In this case, the higher the housing supply elasticity in a municipality where firms are located, the larger the wedge between the equilibrium TFP in that municipality and that of the optimal equilibrium ($TFP_m^B < TFP_m^{max}$). At the same time, it is worth noting that, if all firms were identical in terms of the relative composition of their collateralizable assets, industry TFP would be independent of Φ and, in this case, local housing booms would not create productivity losses.

In line with misallocation models a la Hsieh and Klenow (2009), the variance of the capital-labor ratio in an industry is a sufficient statistic for the TFP within that industry. To obtain closed form solutions, we assume that $M = 1$ and $\kappa = 1/2$. In that case, by plugging equation (1) for the housing boom equilibrium into equation (2), we find that,

$$TFP = \left[\frac{1 - var(k)}{4}\right]^{\frac{\alpha}{2}}. \tag{3}$$

This equation indicates that the higher the variance of capital within an industry, the lower the average TFP. In our case, in the absence of a housing boom the variance of capital would be zero and the average TFP would reach its maximum (technical) level (i.e., an efficient allocation of resources). When a housing boom emerges, the average TFP would be lower, and the higher the local house price appreciation, the lower the TFP (the greater the variance of capital). The magnitude of the aggregate TFP loss would depend on the relative size of the local house price boom and the distribution of firms across these municipalities.

These predictions are derived for a representative industry. The aggregate impact of the collateral channel on productivity in an economy composed of J industries, would simply be the weighted average of the productivity losses within each industry weighted, for example, by the contribution of each industry to the value-added of the economy.

Discussion on asset price booms, capital misallocation and productivity. In this paper, we focus on the impact of local housing booms on the misallocation of capital. However, the same implications for capital allocation and aggregate productivity would emerge if the boom was attached to other collateralizable assets (e.g., financial assets). The root of the misallocation of capital is the artificial increase in the collateral value of some firms, regardless of their productivity. This mechanism arises when the boom in the price of a specific asset changes the relative valuation of collateralizable assets, having the capacity to create an asymmetric access to credit and investment rates across firms that is not related to differences in their idiosyncratic productivities.

4 Data

In this section, we introduce the data used in the empirical analysis implemented in section 5. To test the predictions of the model, we use a rich firm-level panel dataset with detailed information on banking credit records and financial statements of manufacturing firms that were active during the Spanish housing boom. We match this firm-level panel with house prices indices at the municipality-level that are available for the peak of the Spanish housing boom that took place between 2003 and 2007 (Santos, 2014). We complement this matched database with data on buildable urban land at the municipality level for years prior to the housing boom. This database will allow us to use the geographical variation across Spanish municipalities before the housing boom to examine the impact of local house price booms on firms' investment and banking credit. In this section, we also discuss the computation of the main variables used in the empirical analysis, the measurement issues and the relevant assumptions. We defer the discussion of our identification strategy to section 5.

4.1 Financial statements and banking credit data at firm-level

The firm-level data comes from two administrative data sources on business activity and banking credit that we match using the fiscal identifier of firms. The first dataset comes from the unconsolidated financial statements that all firms are required to submit annually by law to the Commercial Registry (*Registro Mercantil Central*). We use the information from the Commercial Registry included in the database built in Almunia, Lopez-Rodriguez and Moral-Benito (2018) for the period 2000-2013, which contains annual information on around 85% of the registered firms in the Spanish non-financial market economy.[15] Figure A.1 in Appendix A shows that, over the 2003-2007 period, the dataset accurately tracks the temporal evolution of production and full-time employment of the manufacturing sector according to official census statistics provided by the Spanish National Statistical Office (*Instituto Nacional de Estadística*). In the same Appendix A, Table A.1 indicates that the sample of manufacturing firms reaches, during the housing boom, an average yearly coverage of 85% for both the aggregate wage bill and the number of firms, and close to 80% for aggregate employment. Lastly, Table A.2 shows that the dataset replicates the firm-size distribution of Spanish manufacturing firms in terms of employment during the housing boom.

This panel dataset includes, among other variables, annual information for each firm on its fiscal identifier, 5-digit zip code of its headquarters, industry code (4-digit NACE Rev. 2 code), average number of employees (full-time equivalent) and the most relevant information contained in the Balance Sheet and the Profit and Loss Account. The main variables used in our empirical analysis included in these financial statements are: (i) net operating revenue; (ii) material expenditures (cost of all raw materials and services purchased by the firm in the production process); (iii) labor expenditures (total wage bill, including social security contributions); (iv) total assets and fixed assets; (v) tangible and intangible fixed assets; (vi) financial expenditures; and (vii) total outstanding debt.

This dataset allows us to compute two firm-level measures of investment: i) the log difference of capital, where capital is measured as the real book value of fixed assets; and ii) the log difference of the capital-labor ratio, where labor refers to wage bill expenditures in real terms. We also compute measures of (i) leverage, computed as the ratio of total outstanding debt to the book value of total assets; (ii) the share of tangible fixed assets, calculated as the proportion of the book value of physical property (real estate assets, factories and equipment) over the

[15]The non-financial market economy includes all sectors of activity excluding those related to public sector activity (e.g., health, education, public security, or administration), mining industries, and the financial activity (e.g., banking or insurance activities). See Almunia, Lopez-Rodriguez and Moral-Benito (2018) for details on the cleaning process and construction of the database, as well as a more exhaustive representativeness analysis of this micro dataset with respect to official statistics of the Spanish economy.

book value of total assets; (iii) financial costs, computed as the ratio of financial expenditures to total outstanding debt; and (iv) firm-level productivity (TFP) estimated using the procedure proposed by Levinsohn and Petrin (2003). Real magnitudes result from deflating nominal values using two-digit industry-specific deflators for capital, output and materials. The measures of the book value of assets are deflated with price indices for investment goods; labor expenditures are deflated using gross output price indices; and material expenditures and value-added are deflated using price indices for intermediate consumption at the industry level. These industry-specific deflators are computed by the Bank of Spain (*Banco de España*) using data from the Spanish National Statistical Office. The sample of manufacturing firms with investment data used in our empirical analysis contains 255,855 firm-year observations corresponding to 71,213 firms in the period between 2003 and 2007.

We merge the annual financial statements database with annual firm-level information on loan applications and total credit exposures to the banking system. These firm-level credit data come from the loan level Central Credit Register (*Central de Información de Riesgos*, CIR) collected by the Bank of Spain in its role of supervisor of the Spanish banking system. This credit register contains detailed monthly information on the credit granted and drawn on new and outstanding loans of more than 6,000 euros to non-financial firms granted by all banks operating in Spain.[16] Using this information, we aggregate this monthly data at the bank-firm-level data to obtain information on the firm's total annual credit granted by the banking system.[17]

The CIR also compiles monthly requests submitted by banks to obtain information on potential borrowers' outstanding debts to all banks and their default status. These requests reveal information about borrowers' applications to banks with which they have no outstanding debt. We use this information to explore the potential impact of the housing boom on the extensive margin of credit. For this purpose, we collect firm-year data on new loans granted by banks as well as firms loan applications to identify those loans granted by banks to non-concurrent borrowers. With this information we compute three annual measures related to the extensive margin of credit: (i) an identifier that takes value one when at least one firm's loan application is accepted by a bank; (ii) the number of loan applications by a firm that are accepted by banks; and (iii) the proportion of new loans of a firm over the total number of loans of this firm granted by banks. The sample of manufacturing firms with banking credit data used in our empirical analysis contains 207,506 firm-year observations corresponding to 61,896 firms in the period between 2003 and 2007.

In Panel A of Table 1 we present summary statistics for the sample of manufacturing firms

[16]The significantly low reporting threshold implies that virtually all firms with outstanding bank debt are included in the CIR database. For a detailed discussion of the CIR database see, for instance, Jiménez et al. (2012).

[17]To undertake robustness exercises, we also create an identifier of the firm's main credit provider in a year to distinguish whether the firm's bank funds come mainly from commercial banks or savings banks.

that are located in municipalities for which we have available data on house prices and the ratio of buildable urban land prior to the housing boom.

4.2 House prices and buildable urban land data at municipality-level

The empirical strategy implemented in the paper requires data on local house prices indices and a measure of urban land availability prior to the housing boom at the municipality level. These data are matched with the firm-level dataset using the geographical location of the firms included in their financial statements.

To capture the dynamics of local housing booms, we use residential house price indices at the municipality level, assuming that the change in those indices well-proxies the evolution of the value of real estate assets owned by firms located in a given municipality.[18] The information on the residential house prices comes from the census of real estate transactions owned by the Spanish Ownership Registry (*Registro de la Propiedad*) and shared by it with the Bank of Spain since 2003. To compute local price indices, we first calculate the market price per square meter for each residential housing transaction and then aggregate those prices for all transactions in a municipality during a year to create a yearly average of prices per square meter. The price indices for residential housing are calculated from 2003 to 2007 for municipalities with more than 1,000 inhabitants and more than 30 transactions per year. These indices are deflated using the Consumer Price Index provided by the Spanish National Statistical Office.

In the discussion of our empirical strategy in section 5, we will justify the need to instrument our measure of house price growth using a proxy of the elasticity of housing supply in the geographic area of our analysis, in line with the procedure followed by Mian and Sufi (2011), Chaney, Sraer and Thesmar (2012) and Basco (2014). To build our instrument, we follow the procedure proposed in Basco, Lopez-Rodriguez and Elias (2022) to compute a proxy of the relative geographic capacity to build new real estate assets in a municipality. This proxy can be calculated in the period prior to the Spanish housing boom as the ratio between the available buildable urban land and the urban land with structures already built. The former magnitude approximates the potential urban land and is defined as total undevelopable land after excluding non-urban protected areas (e.g., rivers or natural parks), plots classified as restricted for rural use, and public goods land (e.g., surface occupied by transportation and utilities infrastructure). The latter magnitude measures the already urbanized land, allowing us to compute a ratio that proxies the relative scarcity of potential urban land. The construction of this ratio follows the insights provided by Glaeser, Gyourko and Saiz (2008) on the impact of geographic supply factors on house price dynamics and adapts to the Spanish case the measure of the housing supply elasticity proposed by Saiz (2010) for the metropolitan areas of the United States.

[18]See subsection 4.3 for a discussion of the empirical evidence on the co-movement of prices in real estate markets in Spain.

The data to construct the proxy of the housing supply elasticity come from the census data on land classifications published by the Spanish Cadastre (*Dirección General del Catastro*). These data allow the computation of the ratio for several years sufficiently removed from the housing boom (from 1995 to 1998) to avoid the feedback effects of booming prices on the availability of developable urban land during the Spanish housing boom. We conjecture that municipalities with a lower buildable urban land ratio (i.e., a lower housing supply elasticity) should have experienced larger increases in house prices during the housing boom. Consistent with this hypothesis, Table C.1 in Appendix C shows that there is a negative cross-sectional correlation between the ratio of buildable urban land (computed for different years) and the growth of housing prices across Spanish municipalities during the peak of the housing boom (2003-2007). We choose the ratio of buildable urban land in 1997 as the baseline in our empirical analysis because using this year we maximize the number of municipalities in the sample with data on both house prices and the measure of buildable urban land.[19]

Our empirical strategy uses the geographical variation in the size of local housing booms to identify the impact of local house price shocks on firms' investment decisions. We illustrate this spatial variation in Figure B.1 of Appendix B for the case of the two provinces with the highest level of economic activity and population in Spain (Madrid and Barcelona). The map plots the cumulative growth rates of real house prices and the buildable urban land ratio at the municipality level within these two provinces. The distribution by municipalities of these magnitudes at the province level is divided into quartiles. Higher house price growth rates are reported with more intense red colours, meanwhile a greater urban land supply is reflected with more intense blue colours. This figure shows the existence of a significant heterogeneity of these magnitudes within provinces, which opens the possibility, in addition to the expected correlation between these magnitudes, of using this geographical variation to identify the causal effects of local housing booms on investment and credit.

In Panel B of Table 1 we present summary statistics on house prices and the pre-boom ratio of buildable urban land for those municipalities whose population exceeds 1,000 inhabitants and that have manufacturing firms included in the sample.

4.3 Measurement Issues

We make several assumptions to overcome the limitations of the available data to accurately measure the impact of local housing booms on the valuation of real estate assets owned by firms. First, in the financial statements we are not able to disentangle the net value of real estate assets from the net value of other tangible fixed assets, particularly, equipment. As an alternative, we use the relative value of tangible fixed assets over total assets as a proxy for the relative weight of collateralizable real estate assets of firms. This is a plausible assumption given

[19]The results of Section 5 are robust when using measures of buildable urban land available for different years (1995, 1996 and 1998).

that our empirical strategy relies on using geographical and time variation in the unit value of these tangible fixed assets owned by firms. We presume that these value changes are mainly driven by local changes in real estate prices over time rather than by changes in the prices of the rest of the tangible fixed assets (e.g., equipment) included in this category.[20] This assumption presumes that the dynamics of equipment prices should not exhibit significant variation across firms within a competitive industry. In addition to this assumption, in our empirical analysis we include industry-year and location (region)-year fixed effects that should absorb unobserved differences in the valuation changes of tangible assets unrelated to the dynamics of local real estate markets.

Second, there are no price indices available at the municipality level for different categories of real estate assets that firms use to own. To overcome this limitation, we assume that real estate markets at municipality level are synchronized and, thus, residential house prices capture the dynamics of the local real estate markets. This assumption of co-movement of prices in real estate markets holds at the aggregate level. Indeed, Figure B.2 in Appendix B shows that aggregate price indices of different real estate assets (commercial real estate, offices, and industry plants) are highly correlated with the residential house price index (e.g., the serial correlation between the time series of different real estate prices is above 0.90 between 2000 and 2012).

Third, financial statements do not provide detailed information on the geographical location of real estate assets owned by firms. We assume that changes in the valuation of firm's collateral are driven by changes in the value of real estate assets located in the municipality where the firm has its headquarters. This assumption seems reasonable given that in Spain small and medium manufacturing firms represent roughly 99% of the census[21], and these firms are almost exclusively single-plants (Almunia et al., 2021). At the same time, although the probability of holding real estate assets in different municipalities is larger among big firms, multi-plant firms are a minority proportion even within this set of business.[22] Lastly, the evidence for the U.S. shows that, for multi-plant firms, the location of headquarters tends to reveal a significant proportion of the value of real estate assets owned by large firms (Chaney, Sraer and Thesmar, 2012).

[20]In robustness subsection 5.4, we perform a sensitivity analysis and a variance decomposition exercise using more detailed real estate collateral data for a subsample of large firms for which we have access to information on the gross book value of land and buildings. The variance decomposition exercise illustrates that, for this subsample of firms, land and buildings drive most of the variation in the tangibility rate, reducing potential biases and concerns about using this variable as a proxy of real estate collateral.

[21]Large firms are defined as those with more than 50 employees (full-time equivalent employment) and they represent approximately 1% of manufacturing firms according to the Spanish National Statistical Office (see Almunia, Lopez-Rodriguez and Moral-Benito, 2018).

[22]The prevalence of single-plant firms among Spanish manufacturing firms has also been discussed in Gopinath et al. (2017). This paper argues that an official survey (*Encuesta Sobre Estrategias Empresariales*) indicates that in Spain during the housing boom just 15% of all large firms in the manufacturing sector were multi-plant firms.

5 Empirical Analysis

This section discusses the identification strategy of our empirical analysis and reports the main results of the paper. The specification of the empirical model is discussed in subsection 5.1, as well as the threads to identification. In subsection 5.2, we provide estimates on the causal impact of local house price shocks on the investment rate of firms through a collateral channel. In subsection 5.3, we explore the causal impact of this collateral channel on both the intensive and the extensive margin of credit allocation. In subsection 5.4, we present estimates that address specific sources of endogeneity that could bias our baseline estimates, and several sensitivity analyses to evaluate the robustness of our results. The set of estimates discussed below support the empirical relevance of the collateral channel on both investment and the allocation of credit among manufacturing firms.

5.1 Specification and identification strategy

The model predicts that when a housing boom occurs firms with a larger share of collateralizable (real estate) assets invest relatively more than firms in the same industry but with a lower share of real estate assets. At the same time, the model predicts that firms with the same relative composition of collateralizable assets are able to borrow and invest more when they are located in areas where house prices increase relatively more. To examine this potential interaction between the relative composition of collateralizable assets and the geographical location of firms, we consider the following empirical model as our baseline specification:

$$Inv_{imt} = \beta_0 + \beta_1 \Delta HP_{mt} + \beta_2 Tang_{imt} + \beta_3 \Delta HP_{mt} * Tang_{imt} + \beta_4 X'_{imt} + \gamma_i + \delta_{srt} + \epsilon_{imt}, \quad (4)$$

where Inv_{imt} is the investment rate of firm i located in municipality m in year t, that is measured by the log difference of the stock of capital between years $t-1$ and t measured in real terms; ΔHP_{mt} is the log-difference of house prices between years $t-1$ and t in the municipality m; $Tang_{imt}$ refers to tangibility rate measured as the share of tangible fixed assets to total assets of firm i located in municipality m in year t; and X'_{imt} is a vector of firms' characteristics.[23]

In order to enhance identification, we include firm fixed effects γ_i that control for unobserved time-invariant firm's characteristics; and a set δ_{srt} of industry-region-year fixed effects. In a first specification, we allow for industry-year fixed effects that control for industry-specific shocks that affect firms within an industry, regardless of their assets composition. In an extended specification, we include industry-region-year fixed effects, in order to also abstract from location (region)-specific shocks that would affect all firms within an industry during a year. Standard errors are clustered at the municipality level.

[23] In subsection 5.4 we discuss the inclusion of a vector X'_{imt} of firms' characteristics to mitigate the existence of potential biases.

The interpretation of this reduced form equation is based on the predictions of the stylized model of investment, discussed in section 3, in which the composition of collateralizable assets of firms interacts with the geographic location of their real estate assets.[24] Consistent with theoretical predictions, the β_3 coefficient measures the differential effect of house prices growth on the investment rate of firms depending on the tangibility of their collateral. In the presence of financial frictions, the model predicts $\beta_3 > 0$, that is, an increase in local house prices raises, for the average firm, the investment rate and the larger the tangibility of firms' assets, the higher the investment rate. The elasticity of house prices growth to the investment rate of the average firm is therefore computed as β_1 plus the interaction of β_3 and the average share of firm's tangible assets.

Equation 4 is informative about the potential effect of local housing booms on investment but it is silent about the financial channel embedded in the model. In our stylized model, firms are financially constrained and their borrowing constraint is related to the value of their collateral. Thus, for a given house price shock, the firm's borrowing capacity increases with its share of real estate assets. To test this financial channel hypothesis, we estimate equation 4 but considering as the dependent variable the net credit growth ΔC_{imt}, measured as the log difference of total banking outstanding credit in real terms between $t-1$ and t of firm i. The model also predicts $\beta_3 > 0$, that is, within an industry, firms with a larger share of real estate assets receive more banking credit when they are located in municipalities that experience higher house price growth.

The OLS estimates of equation 4 could be biased because local house prices are potentially endogenous. Indeed, local house prices can be positively correlated with firms' investment opportunities, and these prices can proxy for local demand shocks. To address this endogeneity concern, we adapt a broadly used empirical strategy in the macro and finance literature that estimates the real effects of house price shocks.[25] Specifically, we run a two-stage least square (2SLS) estimation of equation 4, where house prices at municipality level are instrumented using a proxy of the pre-boom housing supply elasticity in the municipality interacted with the long-term aggregate real interest rate of home mortgages. We use the pre-boom buildable urban land ratio in a municipality, described in section 4, as a proxy for the housing supply elasticity; and, for the long-term aggregate real interest rate, we use the rate of the flow of annual mortgage loans granted to households for the purchase of a house with an initial mortgage term of more than 10 years, from the Bank of Spain between 2003 and 2007.

To show the relevance of our instrument, we run a first-stage regression at the municipality

[24]In line with Chaney, Sraer and Thesmar (2012), the model justifies a specification that regress annual investment rate on current values of the tangibility rate and house price growth. Conditional on repaying debt at the end of a period, firms depend on the valuation of their collateral to obtain funds and invest in the subsequent period.

[25]We follow the empirical strategy used, among others, by Himmelberg, Mayer and Sinai (2005), Mian and Sufi (2011), Chaney, Sraer and Thesmar (2012) or Chakraborty, Goldstein and MacKinlay (2018).

level over the period 2003-2007[26], such that,

$$\Delta HP_{mt} = \alpha_0 + \alpha_1 HSE_m * \Delta R_t + \lambda_t + \tau_m + \xi_{mt}, \tag{5}$$

where ΔHP_{mt} is the log difference of residential house price index in real terms between years $t-1$ and t in the municipality m; HSE_m is the housing supply elasticity in municipality m, proxied by the buildable urban land ratio in a pre-boom year; ΔR_t is the difference in the average long-term real interest rate of home mortgages at national level between years $t-1$ and t; λ_t is a year fixed effect that captures aggregate shocks that could create macro-fluctuations in house prices; and τ_m is a location (municipality) fixed effect that controls for unobserved time-invariant municipality characteristics.

According to economic theory, when there is an aggregate fall in the long-term real interest rate of home mortgages, the demand for houses increases. In municipalities with a larger ratio of pre-boom buildable urban land, the increase in housing demand can be absorbed to a greater extent by the housing supply through expanding construction. Instead, in municipalities with a lower buildable urban land ratio, the increase in demand for housing driven by a fall in real interest rates cannot be fully absorbed by supply and, therefore, it translates into higher house prices. At the same time, in the presence of a housing boom across municipalities, an increase in the real interest rate to curb the housing demand would be more effective in municipalities with higher housing supply elasticity. We thus expect a negative sign in the α_1 coefficient given that a more positive interaction term (larger increase in the real interest rate times higher positive pre-boom buildable urban land measure) is associated with a lower increase in house prices. Table 2 reports the estimates of equation 5 using proxies for the elasticity of housing supply for several years prior to the housing boom (1995, 1996, 1997 and 1998). The estimates show that the coefficient of interest, α_1, is negative and significant at the 1% level for the proxy of the housing supply elasticity in different pre-boom years.[27] The resulting F-tests for the nullity of the instrument are above 10 (see Stock and Yogo, 2005), which indicates the relevance of the instrument and its predictive power on house prices at the municipality level.

5.2 Investment and the housing boom

Table 3 presents OLS and 2SLS estimates of equation 4 for the baseline sample of manufacturing firms. This sample includes firms that i) are active for at least one year during the housing boom (2003-2007); ii) they have a positive stock of capital in the years included in the sample; and

[26] This exercise is simply intended to illustrate the relevance of the instrument to predict the dynamics of house prices across municipalities in Spain. In subsection 5.2, the 2SLS estimates report each of the first-stage F-statistics corresponding to the firm-level regression 4 in which each regressor containing house price growth at the municipality level is instrumented with the interaction of the pre-boom buildable urban land ratio in the municipality and the long-term real interest rate.

[27] In what follows, we use the proxy of the housing supply elasticity in 1997 in order to maximize the coverage of our estimation sample. The estimates provided in the next sections using the 1997 measure are robust when considering alternative pre-boom years to measure the constraints in the buildable urban land of municipalities.

iii) they are located in municipalities where both residential house price indices and measures of housing supply elasticities are available.

The OLS estimates (reported in columns 1 to 3 of Table 3) are consistent with the main prediction of the model. The coefficient on the interaction between local house price growth and the share of tangible fixed assets is positive and significant at the 1% level in all specifications. These estimates point out that the investment rate of the average firm increases when local house prices rise, and the larger the tangibility of firm's assets the larger the increase in the investment rate. The results are robust to the inclusion of firm fixed effects and different sets of industry-location-time fixed effects. The discussion of the empirical results that follows focuses on our preferred specification that includes industry-region-year fixed effects to abstract from location-specific shocks that could affect all firms within an industry during a given year.

According to the OLS estimates of our preferred specification, column (3), the elasticity of house prices growth to the investment rate is -0.04 when the firm has no tangible fixed assets and 0.13 when 100% of the value of firm's assets are tangible assets. Note that these elasticities imply that firms with no real estate assets may be forced to cut investment during housing booms. Quantitatively, these price elasticities imply that moving from the 25th percentile of the distribution of the share of tangible fixed assets to the 75th percentile, increases the investment rate by 4 pp. (0.13x0.31), which represents 45% of the average annual growth of the investment rate in the manufacturing sector (see Table 1).

The OLS estimates of the house price-investment elasticity can be considered a lower bound because of the downward biases discussed in the previous subsection. To overcome this limitation, the identification strategy discussed above allows us to investigate the causal relation between local house prices and investment. The two-stage least square (2SLS) estimates of equation 4 are reported in columns 4 to 6 of Table 3. The F-tests for the nullity of the instruments reported in that table are above 10, which indicates the relevance of the instrument and its predictive power on the growth of house prices in the estimation sample of manufacturing firms.[28] The 2SLS estimates show that the β_3 coefficient of the interaction term remains positive and statistically significant at the 1% level. The magnitude of this coefficient is larger than the OLS estimate, in line with the expected negative sign of the bias created by the endogeneity of house prices.

These results are consistent with the main prediction of the model and indicate a causal relationship between house prices and investment through the collateral channel. In quantitative terms, the estimated impact of house prices on corporate investment is significant. In fact, given a mean tangibility rate of 0.28 in the manufacturing sector, the results of our preferred specification (column 6) imply a house price-investment elasticity for the average manufacturing

[28]The tables reporting the 2SLS estimates include F-statistics of the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple regressors. These statistics refer to the corresponding test for the null hypothesis that the coefficients of the first-stage are equal zero.

firm of 0.13. This elasticity means that a 1% increase in the local house prices leads to a 13% raise in the investment rate for the average firm, in a context of housing boom where the average local house prices increases at 14% per year.[29]

The potential heterogeneous causal impact of local house price shocks on capital accumulation can be illustrated examining the different investment elasticities according to the distribution of the firms' tangibility rate. For instance, given the same local house price shock, manufacturing firms in the 75th percentile of the distribution of the tangibility rate would invest 98 pp more than manufacturing firms in the bottom 25th percentile of this distribution. At the same time, the elasticity of house prices growth to the investment rate is close to 0 for manufacturing firms with a tangibility rate equal to the median (0.234). This result indicates that during housing booms, firms with relatively low tangibility rates, in the presence of the collateral channel, could be forced to cut investment.

The results discussed in this section can be interpreted through the lens of our model as a first evidence of capital misallocation. In fact, once we control for the unobserved time-invariant characteristics of firms, as well as for different industry, time and location specific shocks, investment rates of firms within a manufacturing industry should not depend on either the composition of assets or on the specific geographic location of firms. In contrast, our results indicate that a positive local house price shock creates differential corporate investment rates within an industry that are positively related with the firms' tangibility rate. At the same time, taking into account the share of real estate assets across firms, the investment rates in a given industry depend on the geographic location of firms, i.e. firms located in land-constrained municipalities, which experience larger house price booms, accumulate more capital than firms with the same tangibility rate and in the same industry, but located in municipalities with lower house price growth.

5.3 The credit channel

In this subsection, we explore the potential financial mechanism that can explain the heterogeneous investment patterns associated with the collateral channel documented in the previous section. In the presence of financial frictions, our model predicts that the borrowing capacity of firms depends on the value of their collateral. In this framework, the connection of house prices and credit allocation is a source of capital misallocation through the collateral channel. To empirically explore these predictions, we first examine the impact of local house price shocks on the intensive margin of credit. Then, we provide some suggestive evidence on the potential

[29]To put this result in the context of the literature, the estimates reported in Chaney, Sraer and Thesmar (2012) situate the house price-investment elasticity at 6% for the average firm in the estimation sample for the U.S. The larger magnitude of this elasticity for Spanish manufacturing firms could be consistent with an economy with greater financial frictions where small and medium firms, whose relative presence in the estimation sample is greater than in Chaney, Sraer and Thesmar (2012), depend more on collateralizable assets to obtain credit in order to finance their investment projects (see discussion in subsection 5.3)

impact of the collateral channel on different measures that proxy the extensive margin of credit.

Table 4 presents the OLS and 2SLS estimates of equation 4, for the baseline sample of manufacturing firms that have outstanding debt to the banking sector, using net credit growth as the dependent variable instead of the investment rate. Net credit growth is measured as the log yearly difference of total banking outstanding credit in real terms.

The OLS estimates (reported in columns 1 to 3 of Table 4) cannot reject the prediction of the model that relates (banking) credit allocation to the tangibility of firms' collateral. In all OLS specifications, the coefficients of the interaction term between the tangibility rate and the local house price growth are positive and significant at the 1% level. The OLS estimates of the house price elasticity for credit in the manufacturing sector are quantitatively similar to those obtained for the investment rate. For instance, the relative scarcity of real estate assets that can be used as collateral (e.g. a tangibility rate in the first quartile of the distribution) correlates with a lower allocation of banking credit among manufacturing firms.

The potential endogeneity of house prices, concern discussed in detail above, could also bias the house price elasticity of credit downwards. To address this concern, the 2SLS estimates reported in Table 4 (columns 4 to 6) adopts the instrumental variables strategy discussed in subsection 5.1. The results on the F-tests show, in the first place, the relevance of the proposed instrument also in the sample of manufacturing firms that have outstanding debt with the banking sector. Second, the second-stage estimates of the interaction term, once we control for firm fixed effects and different sets of industry-location-time fixed effects are consistent with the theoretical predictions. These estimates indicate a greater positive effect of house price growth on banking credit for firms with a larger tangibility rate. The estimates reported in our preferred specification (column 6) show a quantitatively and statistically significant house price-credit elasticity for the average manufacturing firm of 0.29. The elasticity for the median manufacturing firm is also quantitatively significant and stands at 0.21.

The 2SLS estimates indicate that the magnitude of the causal impact of local house prices shocks on credit is slightly larger than the impact on investment discussed above. The larger impact is noticeable when comparing the house price elasticity of the average manufacturing firm (0.29 for credit versus 0.13 for investment). This sizeable elasticity of credit at the firm level in a context of high house price appreciations is compatible with the quick rise in the leverage ratio observed in the Spanish manufacturing sector over these years.

The heterogeneous impact of local house prices on corporate credit is also relevant in terms of the distribution of collateralizable real estate assets. For instance, the effect of moving a firm from the 25th to the 75th percentile of the tangibility rate distribution implies an additional credit growth rate of 53pp for the same local house price shock. This evidence on the differential allocation of credit related to the relative value of real estate assets is consistent with the hypothesis that the collateral channel is a relevant mechanism through which house prices distort the allocation of capital. Specifically, these results point out a misallocation of banking credit within manufacturing industries towards i) firms located in areas with larger local house prices shocks; and ii) firms with a larger share of collateralizable real estate assets.

As a complementary result, in Table 5 we examine the potential impact of local house price shocks on the extensive margin of credit. To explore this channel, we focus on firms that had a credit relation with at least one bank in the years of the housing boom. We consider the baseline specification in equation 4 but now we use three alternative dependent variables. In particular, dependent variable in columns 1 and 2 is a dummy that takes value 1 for firm i when at least one new loan application is accepted by a bank; dependent variable in columns 3 and 4 is the number of new loan applications of firm i that are accepted by banks; and dependent variable in columns 5 and 6 is the proportion of new loans over the total number of loans granted by banks to firm i.

The OLS estimates of the coefficient of the interaction term in the linear probability model (LPM)[30] in Table 5 (column 1) is positive and statistically significant at the 5% level. This result suggests that firms in booming municipalities and with more tangible assets were more likely to start a new lending relationship with a bank. The 2SLS estimates of the LMP (column 2) aim to deal with the potential downward bias in the estimated coefficient created by the endogeneity of house prices. In spite of the relevance and significant predictive capacity of the instrument, as revealed by the F-tests associated with the first-stage coefficients, the increase in standard errors makes the larger coefficient of the interaction term not statistically significant. However, the 2SLS estimates of the interaction term in the specifications that use alternative measures commonly used in the empirical banking literature to examine the extensive margin of credit are quantitatively and statistically significant at 5% (columns 4 and 6). These estimates show that local house price shocks increased both the number of new loans and the proportion of new loans to total loans more for firms that had a larger proportion of collateralizable real estate assets. Thus, these results are consistent with an impact of the collateral channel on the allocation of banking credit also in the extensive margin.[31]

[30]In the context of our empirical strategy, adopting a LPM allows us to control for multiple fixed effects and address the endogeneity issues by implementing an instrumental variables estimator. The simultaneous consideration of these two dimensions confers an advantage to the LPM compared to alternative non-linear discrete choice models that in this context face methodological limitations (see, for instance, Arellano and Honoré, 2001 and Arellano and Bonhomme, 2011). This estimation procedure is in line with the empirical banking literature that has usually adopted the LPM to explore the extensive margin of credit to avoid an incidental parameters problem and to obtain consistent causal estimates (see, for instance, Jiménez et al., 2014).

[31]In Online Appendix C.1, we include estimates of running a Poisson pseudo-likelihood (PPML) regression with multiple levels of fixed effects to provide additional sensitivity analysis to our extensive margin results. Table C.2 shows that the qualitative estimates of the PPML model are consistent with the OLS estimates of the LPM, and therefore these results indicate that the collateral channel also operated in the extensive margin of credit.

5.4 Robustness

In this subsection we summarize the set of sensitivity analysis that we undertook to evaluate the robustness of our findings. The tables reporting the main estimates and a more detailed discussion of these exercises are included in the Online Appendix C.2 (Tables C.3 to C.25).

First, we explore the possible heterogeneous impact of the collateral channel depending on the firm size or which bank is the main credit provider for firms. To rule out that our estimates are driven by a specific segment of the demand for capital associated with the size of the firm, we undertake three empirical exercises. Tables C.3 and C.4 show that our results are robust to the introduction of different log firm size measures (in terms of employment, sales and assets) as controls. Tables C.5 and C.6 report WLS estimates of our baseline investment and credit equations weighting observations by measures of firm size during the housing boom. The WLS estimates discard the possibility that the average estimates were driven only by the smallest firms, which would reduce the aggregate relevance of the collateral channel. Finally, Tables C.7 and C.8 show estimates of the collateral channel in samples for small, medium and large firms defined in terms of employment. The results show a stronger response for medium-sized firms (21-49 employees) and a lower response for large firms, although the results for large firms are significant at the 10% level. Regarding the credit supply, we test the hypothesis that credit allocation among firms was driven by the lending policy of politically oriented savings banks (Fernández-Villaverde, Garicano and Santos, 2013). The estimates in Table C.9 show that there is not statistically significant difference between the estimates of the sample of firms whose main credit provider is commercial banks and the estimates when the main provider is savings banks. This set of robustness analysis implies that our collateral channel estimates do not stem from a particular segment of the capital demand or the supply of credit.

Second, we expand our baseline specification to control for time-varying firm-level variables that can be confounding factors of both investment and credit, and could also be related to both the valuation of corporate collateral and our instrument for local house price shocks. Tables C.10 and C.11 show that our estimates are robust to the inclusion of covariates that control for firms' financial conditions (the leverage ratio and financial costs), as well as to the inclusion of firms' productivity shocks that control for the supply determinants of capital accumulation. To discard that our results are driven by the reallocation of capital towards low-productivity firms with higher tangibility rates, we explore the relevance of the collateral channel into two subsamples of high- and low-productivity firms based on their relative position to the median of the TFP-sales measure. The estimates reported in Tables C.12 and C.13 show that the collateral channel has a casual impact on the relative allocation of capital within each firms' productivity group, which rejects a systematic correlation between capital accumulation through the collateral channel and the productivity of firms. Finally, Table C.14 shows that including firm productivity as a covariate has a minor impact on the relevant coefficients in the analysis of the extensive margin of credit.

Third, we examine the potential impact of other sources of endogeneity on our main results. To consider the endogeneity created by the real estate ownership decision and its potential relation with investment and credit demand, we first explore predictors of the firms' tangibility rate. Table C.15 shows that the initial level of total assets in 2002 is a good predictor of the pre-boom tangibility rate of firms, indicating that larger firms have lower tangibility rates. Table C.16 shows the estimates of our baseline regression when adding these predictors of the firm tangibility rate (initial log asset value quintiles) interacted with the log change in house prices as controls. Our main estimates are robust to the inclusion of these controls, which produce minor changes in the house prices elasticities of investment and credit. An alternative challenge to the consistency of our estimates arises when large firms are located in geographic areas where their investment decisions may have a large impact on house prices and economic activity. To examine this potential source of bias, Tables C.17 and C.18 report estimates when restricting our sample to small and medium-sized firms (i.e., less than 50 employees) that are located in municipalities whose population in 2002 exceeds certain population thresholds (5,000, 10,000 and 50,000 inhabitants). The estimates are robust to these sampling restrictions, which suggests that firms do not have the capacity to affect the dynamics of local house prices with their input decisions.

Finally, we perform additional robustness tests on our main estimates. Table C.19 shows that our results are robust when using the log change in the capital-labor ratio as an alternative definition of the investment rate. The estimates in Table C.20 discard that our main results are significantly affected when excluding from the estimation sample the subsidiaries of foreign multinationals that operate in Spain. Table C.21 shows minor effects on the efficiency of our estimates when clustering standard errors at different levels. Tables C.22 and C.23 report the main investment and credit estimates considering firms active in all industries included in the non-financial market economy. Our results are qualitatively robust when these industries are included, indicating that the collateral channel is a mechanism that generates capital misallocation within industries beyond its impact on the manufacturing sector. Lastly, we examine the robustness of our results using an alternative proxy of real estate collateral computed for a subset among the largest firms that report more detailed information on the gross book value of land and buildings. Tables C.24 and C.25 show estimates using this alternative proxy when it is available for a subsample of firms active, respectively, in the manufacturing industries and the non-financial market economy. The estimates for each subsample show the theoretically expected sign of estimated coefficients with different levels of statistical significance that can be affected by relatively small sample sizes. However, these results should be considered with caution given the data limitations to calculate an accurate measure of net real estate collateral and the selection of the sample towards the largest firms. In addition to this robustness, we perform a variance decomposition exercise for the subsample of large firms for which we can proxy their relative composition of tangible fixed assets between real estate and equipment assets. This exercise indicates that the gross book value of land and buildings contributes in the range of 65% to 75% to the share of the explained variance of an OLS model that regress the tangibility rate on this proxy of real estate collateral, a relative measure of gross equipment assets and multiple fixed effects as specified in our baseline regression. This contribution reaches 60% of the variation in a smaller subsample for manufacturing industries. These results show that among the largest firms, which on average have a lower relative weight of tangible fixed assets, the land and buildings component explains most of the variation in the collateral proxy used in our regressions (i.e., the tangibility rate).

6 Aggregate Effects

In this section, we provide suggestive evidence on the aggregate effects of local house price booms on the misallocation of capital within industries using the suitable case of the Spanish housing boom. To examine the aggregate impact of a housing boom through the collateral channel on investment, as indicated by predictions 2 and 3 derived in section 3, we perform two complementary exercises. First, we undertake a growth accounting exercise guided by our model to quantify the decline in aggregate TFP in response to an increase in the variance of the capital-labor ratio driven by a housing boom. Second, we carry out a back-of-the-envelope exercise to approximate the contribution of the collateral channel on investment to the decline in aggregate TFP between 2003 and 2007 in Spain.

In line with misallocation models *à la* Hsieh and Klenow (2009), our stylized model delivers a relationship between aggregate TFP and the dispersion of the capital-labor ratio (see equation 3). Assuming that the collateral channel created by local housing booms is the only channel that drives the actual increase in the dispersion of the capital-labor ratio within industries, we can use our model to undertake a growth accounting exercise for the Spanish economy during the period 2003-2007. To perform this accounting exercise, we first log-differentiate equation 3 and plug into it an increase in the dispersion of the capital-labor ratio of 10.9%, a figure obtained by calculating this magnitude from the micro data for the Spanish non-financial market economy. This increase in dispersion implies, according to our model, that aggregate TFP decreased by 2.67% in cumulative terms between 2003 and 2007, which represents an annual decline in aggregate TFP of 0.67% during this period.[32] Using the data in the National Accounts to calculate the actual share of capital (0.49) and the actual cumulative growth of the output per employee in Spain between 2003 and 2007 (-1.55%), the computed decline in aggregate TFP during this period would be consistent with an annual increase in the aggregate capital-labor ratio of 0.57%. That is, according to our model that relates the TFP dynamics and the

[32]To obtain this result, note first that the log-differentiation of equation 3 is $\hat{TFP} = -\frac{\alpha}{2}\hat{var}(k)$, where $\hat{TFP}$ is the growth rate of TFP and $\hat{var}(k)$ is the growth rate of the variance of the capital-labor ratio. We then compute the change in TFP considering that the capital share (α) is equal to 0.49, calculated using current prices data of the gross value added and the compensation of employees in the market economy according to the National Accounts, and assuming a Cobb-Douglas production function as discussed in section 3. The average annual decline in TFP calculated in the numerical exercise is close to the actual annual decline of -0.55 according to the National Accounts as reported in EUKLEMS (Stehrer et al., 2019).

housing boom, the collateral channel on investment would have had the capacity to contribute to a capital deepening of the Spanish economy. This decomposition of economic growth in which the economic expansion is driven by capital deepening despite declining aggregate TFP is consistent with alternative growth accounting analyzes for Spain during this period discussed in the related literature (see, for example, Garcia-Santana et al., 2020 and Gopinath et al., 2017).

In the growth accounting exercise, we assumed that the collateral channel triggered by the housing boom had the capacity to account for all of the actual increase in the dispersion of the capital-labor ratio. In a complementary exercise, we now perform a simple counterfactual quantification of the contribution of the collateral channel on investment to the decline in aggregate TFP during the Spanish housing boom.[33] To undertake this approximation, we first need to compute the effect of house prices on the dispersion of the capital-labor ratio within industries. To obtain reduced-form estimates of this relationship, we divide the sample of firms into municipality-industry pairs for each year between 2003 and 2007. For each pair, we compute the variance in the log of the capital-labor ratio in real terms. We then run the following regression,

$$logVar(K/L)_{mst} = \beta_0 + \beta_1 logHP_{mt} + \delta_{srt} + \epsilon_{mst}, \tag{6}$$

where $Var(K/L)_{mst}$ is the variance of the log of the capital-labor ratio in real terms in municipality m, industry s and year t, HP_{mt} is the average house price index in real terms in municipality m at year t, and δ_{srt} is a set of industry s, region r and year t fixed effects. Standard errors are clustered at the municipality level. The model predicts $\beta_1 > 0$.

Table 6 reports the estimates of the coefficients in equation 6 when including different sets of fixed effects. In columns 1 to 3, the estimation sample includes industry-municipality pairs in the manufacturing sector, and in columns 4 to 6 the estimation sample is expanded to include all municipality-industry pairs in the non-financial market economy. In columns 1 and 4, we consider year fixed effects to capture macro-aggregate conditions that commonly affect municipality-industry pairs. In columns 2 and 5, we include industry-year fixed effects, which allow us to control for industry-specific shocks that affect industries regardless of their geographic location. In columns 3 and 6, we add industry-region-year fixed effects, to also account for common shocks within industries that may be location (region) specific. The sign of the house price coefficient is positive and statistically significant in all columns. The magnitude of the coefficient for the sample restricted to manufacturing industries ranges from 0.39 to 0.53 depending on the set of fixed effects included in the specification, and this range is very similar, from 0.34 to 0.50, when considering all the industries in the non-financial market economy.

[33] The estimates discussed in section 5 identify a positive causal relationship between larger valuations of firms' real estate assets, due to local house price shocks, and capital accumulation among firms. This collateral channel creates capital misallocation within industries, as shown by the estimates reported in Table C.19.

These estimates imply that a one percent increase in local house prices is associated with an increase in the dispersion of the capital-labor ratio of industries at the municipality level of approximately 0.4-0.5 percent. The specification that includes industry-region-year fixed effects is our preferred one for examining the relationship between local housing booms and capital misallocation within industries. These estimates show the existence of a positive correlation between local house price shocks and the dispersion across the geographical space of the log of the capital-labor ratio within industries. This suggestive evidence is consistent with the theoretical prediction that indicates a larger increase in the dispersion of capital in a given industry in municipalities that experienced a larger increase in house prices, revealing a misallocation of resources.

The second required component in our quantification is a measure of the aggregate house price distortion caused by the housing boom. At the empirical level, an important challenge to compute the aggregate effect of heterogeneous local housing booms is the difficulty of measuring the actual size of the house price shock to the economy. To mitigate this limitation, we follow Glaeser, Gyourko and Saiz (2008) and Mian and Sufi (2011) that examine the heterogeneous nature of local housing booms by classifying municipalities into quartiles according to the distribution of initial housing supply constraints. In our setting, we make the conservative assumption that the average size of the house price shock in the economy can be proxied by the differential average growth rate in the mean price of houses located in the first and the fourth quartiles of the pre-boom buildable urban land ratio distribution of the municipalities in Spain. When there is a housing boom, the path of house prices in the first quartile of municipalities should be closer to its fundamental level, while prices should grow more in land-constrained areas. Therefore, we assume that the difference in the mean house prices of these two groups is the proxy for the aggregate average effect of the housing boom on house prices. According to the data, the differential growth in average house prices between the first and fourth quartiles during the housing boom (2003-2007) was 9% in real terms.

Lastly, using the coefficients reported in Table 6, that measure the increase in the capital-labor ratio variance associated with a 1% increase in log house prices, and our proxy for the aggregate increase on house prices (9%), we compute the increase in the variance of the capital-labor ratio due to the housing boom. The coefficients reported in columns 4 to 6 in Table 6, for the estimation sample that includes all industries in the market economy, imply that the housing boom can explain an increase in the variance of the capital-labor ratio that ranges between 3.1% and 4.5%, the latter being the increase inferred from our preferred specification (column 6). Given that the actual increase in the variance of the log capital-labor ratio in Spain between 2003 and 2007 was 10.9%, our quantification indicates that the housing boom could account for between 28.5% and 41.5% of the increase in the dispersion of capital among all Spanish industries in the market economy during this period. Considering our preferred specification and the one-to-one theoretical mapping between changes in the variance of the log capital-labor ratio and changes in TFP, this back-of-the-envelope computation indicates that the differential growth of local house prices (created by the housing boom) can account for around 40% of the decline in aggregate productivity in the Spanish market economy during the housing boom.[34]

Through the lenses of our model, the housing boom affects aggregate productivity when the change in the valuation of corporate collateral driven by local house price shocks is heterogeneous within the same industry. In this case, firms that received larger positive shocks to the valuation of their real estate assets had the ability to accumulate more capital regardless of their productivity. Thus, local housing booms increase the dispersion of the capital-labor ratio within industries revealing misallocation of capital and contributing to reduce aggregate TFP. At the same time, the collateral channel affects the geographical allocation of capital. Municipalities that experience higher appreciations in house prices accumulate more capital because the collateral value of firms located in these municipalities increases relatively more. This spatial channel of capital misallocation is in line with the geographic channel of misallocation emphasized in Hsieh and Moretti (2019) that show the impact of local restrictions on housing supply as a mechanism that creates spatial labor misallocation in metropolitan areas of the United States.

7 Concluding Remarks

In this paper, we provided empirical evidence on the contribution of local house price booms to create capital misallocation within industries. Spain experienced a salient housing boom in the late 2000s that coincided with an outstanding expansion of corporate investment and banking credit. We documented that during the peak of this housing boom, firms that had a larger proportion of tangible fixed assets obtained more banking credit and their investment grew more intensively. Using municipality-level geographical variation on house prices and urban land supply, we showed that this collateral channel on investment and credit was exacerbated when firms were located in land-constrained areas, which experienced higher house price growth.

This paper points to the geographical conditions that shape real estate markets as a potential source that creates industry misallocation of resources through the heterogeneous impact of local house prices on firms' collateral. We documented the existence of capital misallocation during the Spanish housing boom, measured as an increasing dispersion of the capital-labor ratio within industries, and related it to differential local house price shocks that affected the relative valuation of assets owned by firms in a heterogeneous way. Our empirical findings are consistent with the collateral channel on corporate investment created by real estate shocks documented for the United States by Chaney, Sraer and Thesmar (2012). The novelty of the paper relies on linking this channel with the geographical conditions on local housing markets,

[34] An analogous back-of-the-envelope exercise for the manufacturing sector, using the estimates in columns 1-3 of Table 6 and the proxy for the aggregate house price shock (9%), implies that the housing boom could explain between 35 and 50% of the TFP decline in this sector between 2003 and 2007.

where collateralizable real estate assets are located, as a source of capital misallocation within industries. This geographical dimension of misallocation could be a channel that contributes to create aggregate TFP losses during housing booms. Using our reduced-form estimates and guided by our theoretical model, we performed a simple counterfactual calculation indicating that during the Spanish housing boom the misallocation of capital generated by the collateral channel on investment could have accounted for around 40% of the fall in TFP experienced by the Spanish economy during the peak of the housing boom.

The results on the relationship between house prices and capital misallocation do not depend on the nature or mechanism that originates the housing boom. However, one possible interpretation of our results is that we would have identified a micro-mechanism through which capital inflows can create aggregate capital misallocation within industries when these inflows are associated with local housing booms. In this sense, we would provide a micro-mechanism to the aggregate misallocation generated by capital inflows documented in Gopinath et al. (2017) for Southern European economies during the first decade of the 2000s. Finally, it may be interesting to explore the interdependencies between the collateral channel created by real estate booms and the potential exacerbation that could arise in low interest rate contexts. For instance, a decline in global interest rates may lead to housing booms (search for yield) and, in addition, this reduction in the cost of borrowing may be biased towards collateralized loans. In principle, both effects should be conducive to create misallocation, but we leave a quantitative analysis of this question for future research.

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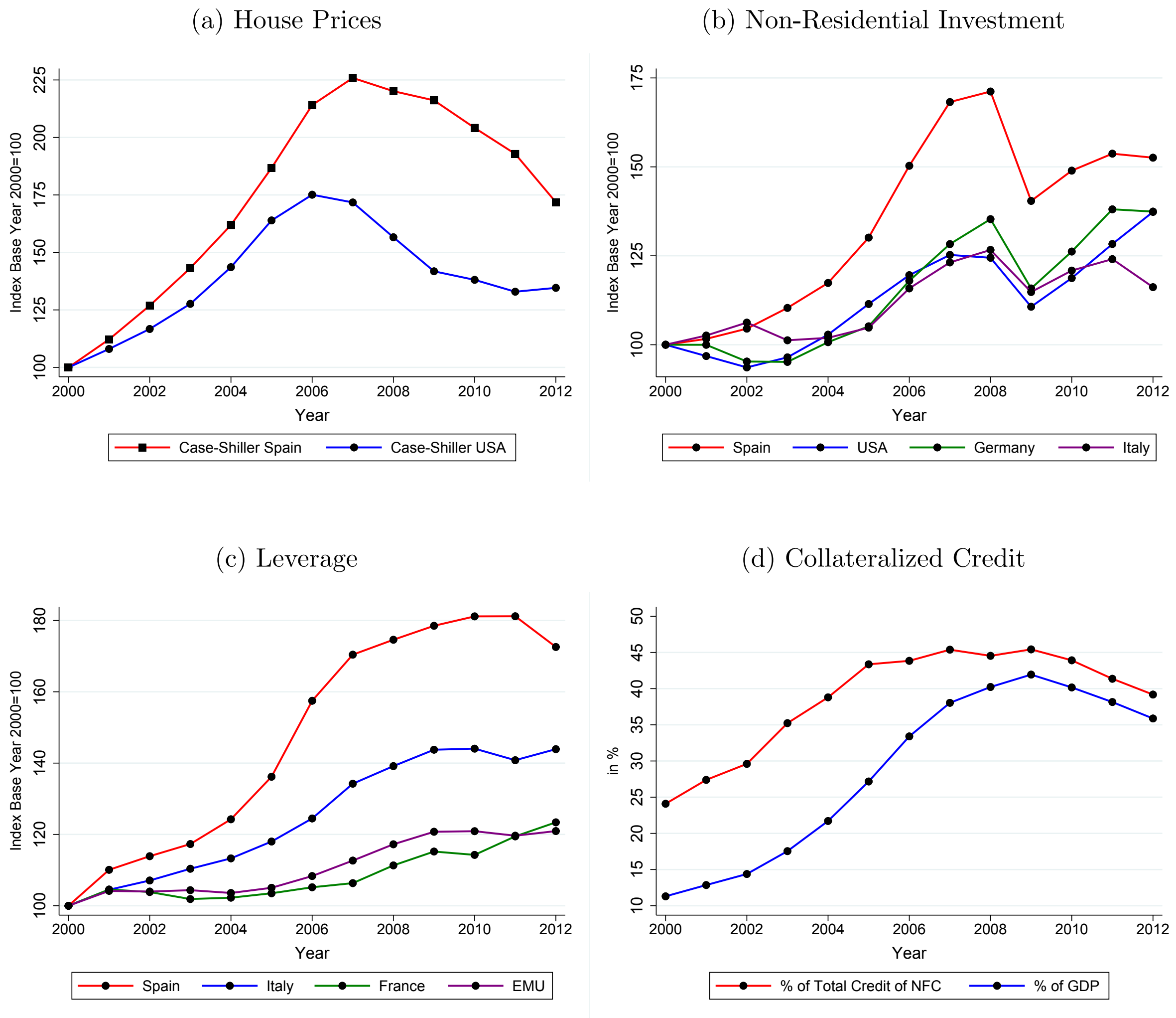
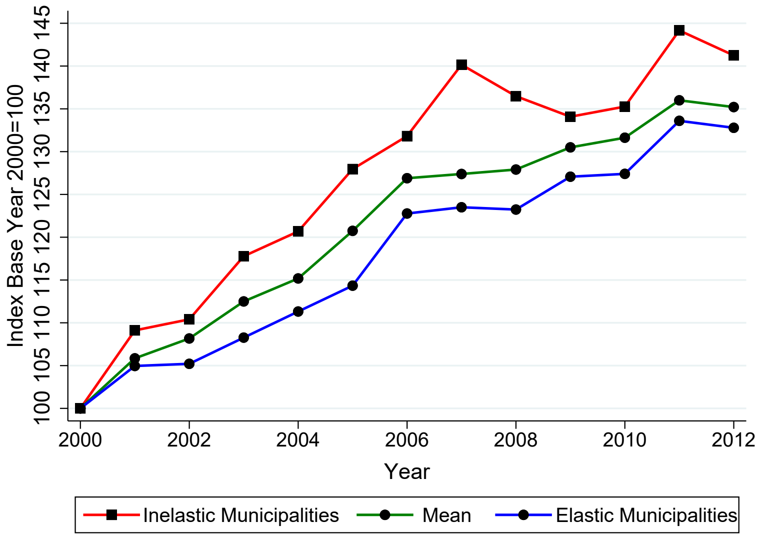
Figures

Figure 1: House Prices, Investment, Leverage and Collateralized Credit



Note: Panel (a) plots the seasonally adjusted Case-Shiller home price index in nominal terms for Spain and the U.S. from 2000 to 2012, using 2000 as the base year. Data for Spain come from the Spanish Ownership Registry, and data for the U.S. come from the Federal Reserve Bank of St. Louis. Panel (b) plots gross fixed capital formation, using 2000 as the base year, excluding investment in dwellings and other buildings and structures (roads, bridges, airfields, or dams) to proxy non-residential investment by the private sector. Data come from the OECD database on Investment by asset. Panel (c) plots the aggregate leverage ratio of non-financial corporations, defined as the ratio of debt (banking credit and corporate bonds) as a percentage of GDP, using 2000 as the base year. Data come from the Eurosystem. Panel (d) plots the collateralized credit granted to non-financial corporations as a percentage of total credit granted and as a percentage of GDP. Data come from the Bank of Spain.

Figure 2: Misallocation of Capital



Note: Figure plots the annual weighted averages of the variance of the log of the real capital-labor ratio for firms in the non-financial market economy from 2000 to 2012. The averages are reported for both elastic and inelastic municipalities, as well as for the mean of Spanish municipalities with a population of more than 1000 inhabitants. Elastic (inelastic) municipalities are those that are above the 75th (below the 25th) percentile in the municipalities' distribution of the ratio of buildable urban land in Spain in 1997. The averages are obtained by weighting the variance of the log of the real capital-labor ratio of each firm by the firm production's share in the aggregate production of firms located in elastic or inelastic municipalities. The mean for Spain weights firms' variance of the log of the real capital-labor ratio by the firms' share in the aggregate production of the Spanish municipalities with a population of more than 1000 inhabitants. Data come from the Bank of Spain and the Spanish Cadastre.

Tables

Table 1: Summary Statistics

	Mean	SD	25th	Median	75th	Observations
Panel A. Firm Dataset						
Share of Tangible Fixed Assets	28.03	21.10	10.59	23.35	41.60	255,855
Capital-Labor Ratio	1.62	2.51	0.38	0.89	1.91	255,763
Leverage Ratio	0.64	0.30	0.42	0.66	0.85	241,608
Employment	16.85	24.81	4	9	19	239,976
Financial Costs	4.23	6.78	1.07	2.62	4.89	243,213
Yearly Investment Rate	0.09	0.60	-0.16	0.00	0.10	255,855
Yearly Credit Growth	0.16	0.70	-0.18	-0.03	0.25	207,506
Cumulative Investment Rate	0.79	5.26	-0.32	-0.03	0.62	36,950
Cumulative Credit Growth	1.16	7.09	-0.25	-0.18	0.99	31,245
Panel B. Municipality Dataset						
Yearly House Prices Growth	0.14	0.33	0	0.10	0.22	7,824
Cumulative House Prices Growth	0.55	0.58	0.27	0.48	0.71	1,567
Buildable Urban Land Ratio	0.75	1.11	0.31	0.55	0.88	2,309

Note: Panel A presents summary statistics for the sample of manufacturing firms located in municipalities where data on residential house prices and the ratio of buildable urban land are available. This panel first reports summary statistics of the annual data of firms in the period 2003-2007 on i) the share of tangible fixed assets, calculated as the proportion of the book value of physical property (real estate assets, factories and equipment) over the book value of total assets as reported on firm's balance sheet; ii) the capital-labor ratio, measured as the ratio of the book value of fixed assets to the wage bill; iii) the leverage ratio, computed as the ratio of the total outstanding debt to the book value of total assets; iv) the average number of employees (measured as full-time equivalent employment); and v) financial costs, computed as the ratio of financial expenditures to total outstanding debt. The panel then presents summary statistics for firms on their yearly investment rate and their yearly credit growth, which refers to the annual growth rate of, respectively, the real book value of fixed assets and the firm's outstanding credit with the banking system during the period 2003-2007. The panel also presents the cumulative growth rate of credit and the investment rate from 2003 to 2007 for those firms included in the sample during those specific years. Panel B presents summary statistics for those municipalities with a population of more than 1,000 inhabitants and that have manufacturing firms included in the sample. Yearly house price growth refers to the annual growth rate of municipal house price indices in real terms during the period 2003-2007. Cumulative house price growth denotes the growth rate of municipal house price indices in real terms from 2003 to 2007. Buildable urban land ratio refers to the ratio between the potential urban land surface and the surface of urban land with structures already built in 1997.

Table 2: Buildable Urban Land and House Prices

Dependent variable:	Δ Ln(House Prices)			
	(1) 1995	(2) 1996	(3) 1997	(4) 1998
Buildable Urban Land Ratio ×	-0.023***	-0.023***	-0.026***	-0.031***
Δ Real Interest Rate of Mortgages	(0.007)	(0.007)	(0.008)	(0.008)
Year FE	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
F-Statistic	11.94	9.79	11.54	15.73
Municipalities	1,854	1,854	1,854	1,854
Observations	6,594	6,594	6,594	6,594

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes municipalities where i) manufacturing firms are active for at least one year in the period 2003-2007; and ii) residential house price indices and measures of housing supply elasticities are available. The dependent variable is the municipality's annual house prices growth, which is measured by the log difference of the average price index in real terms of residential house prices between the years $t-1$ and t in the municipality m. The buildable urban land ratio is the proxy for the housing supply elasticity computed for a municipality m in years prior to the housing boom and calculated according to the procedure described in Basco, Lopez-Rodriguez and Elias (2022). The change in the real interest rate of mortgages is computed using the average annual rate of the flow of mortgage loans granted to households for the purchase of a house with an initial mortgage term of more than 10 years from 2003 to 2007. The data on these mortgage interest rates are provided by the Bank of Spain. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 3: House Prices and Investment

Dependent variable:	Investment					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ Ln(House Prices)	-0.044***	-0.044***	-0.045***	-0.657***	-0.737***	-0.760**
	(0.016)	(0.016)	(0.016)	(0.219)	(0.232)	(0.297)
Tangibility	0.927***	0.927***	0.929***	0.659***	0.634***	0.631***
	(0.025)	(0.025)	(0.025)	(0.043)	(0.045)	(0.045)
Δ Ln(House Prices) × Tangibility	0.131***	0.133***	0.134***	2.878***	3.143***	3.181***
	(0.038)	(0.038)	(0.038)	(0.412)	(0.438)	(0.439)
Observations	186,650	186,650	186,602	186,650	186,650	186,602
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Industry-Year FE	No	Yes	No	No	Yes	No
Industry-Region-Year FE	No	No	Yes	No	No	Yes
1st Stage F-Stat. on IV-1				16.46	16.14	10.48
1st Stage F-Stat. on IV-2				45.93	45.60	47.33

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have a positive capital stock in the years included in the sample. For any X, $\Delta \text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 to 3 report Ordinary Least Squares (OLS) estimates, and columns 4 to 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 4: House Prices and Banking Credit

Dependent variable:	ΔLn(Credit)					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ Ln(House Prices)	-0.040**	-0.039**	-0.045**	-0.111	-0.135	-0.185
	(0.019)	(0.019)	(0.018)	(0.372)	(0.386)	(0.459)
Tangibility	0.246***	0.245***	0.248***	0.090*	0.081	0.094*
	(0.029)	(0.029)	(0.029)	(0.054)	(0.056)	(0.056)
Δ Ln(House Prices) ×	0.116**	0.116**	0.123***	1.751***	1.826***	1.711***
Tangibility	(0.046)	(0.046)	(0.047)	(0.445)	(0.462)	(0.460)
Observations	158,522	158,522	158,477	158,522	158,522	158,477
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Industry-Year FE	No	Yes	No	No	Yes	No
Industry-Region-Year FE	No	No	Yes	No	No	Yes
1st Stage F-Stat. on IV-1				13.82	13.63	9.06
1st Stage F-Stat. on IV-2				42.04	42.12	43.66

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 to 3 report Ordinary Least Squares (OLS) estimates, and columns 4 to 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 5: House Prices and Extensive Margin of Credit

Dependent variable:	Acceptance of a New Loan Application					
	Acceptance Dummy		Number of Loans		Proportion of Loans	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.018	-0.218	-0.011	-0.129	-0.008	-0.149
	(0.012)	(0.268)	(0.016)	(0.373)	(0.005)	(0.104)
Tangibility	0.044***	0.026	0.044**	-0.023	0.026***	0.009
	(0.015)	(0.027)	(0.021)	(0.039)	(0.007)	(0.011)
Δ Ln(House Prices) ×	0.064**	0.241	0.065	0.750**	0.031**	0.201**
Tangibility	(0.032)	(0.223)	(0.041)	(0.345)	(0.013)	(0.091)
Observations	186,602	186,602	186,602	186,602	186,602	186,602
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		10.48		10.48		10.48
1st Stage F-Stat. on IV-2		47.33		47.33		47.33

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta \text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable in columns 1 and 2 is a dummy that takes value 1 for firm i when a bank accepts at least one new loan application. The dependent variable in columns 3 and 4 is the number of new loan applications from firm i that are accepted by the banks. The dependent variable in columns 5 and 6 is the proportion of new loans over the total number of loans granted by banks to the firm i. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table 6: Misallocation at the municipality level

Dependent variable:	Variance of log capital-labor ratio					
Sample:	Manufacturing Sector			Non-Financial Market Economy		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Housing Prices)	0.388***	0.503***	0.534***	0.345***	0.420***	0.497***
	(0.039)	(0.053)	(0.056)	(0.026)	(0.034)	(0.037)
Observations	35,041	35,039	34,878	78,987	78,987	78,478
Year FE	Yes	No	No	Yes	No	No
Region-Year FE	No	Yes	No	No	Yes	No
Industry-Region-Year FE	No	No	Yes	No	No	Yes

Note: Standard errors clustered at the municipality level in parenthesis. The dependent variable is the log variance of the capital-labor ratio in real terms in the municipality m, industry s and year t. House prices denote the log of the average price index in real terms of residential housing in the municipality m and the year t. In columns 1 to 3, the estimation sample includes industry-municipality pairs in the manufacturing sector active in at least one year during the period 2003-2007. In columns 4 to 6, the estimation sample includes industry-municipality pairs in the non-financial market economy active in at least one year during the period 2003-2007. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Online Appendix
Not Intended for Publication

"House Prices and Misallocation:

The Impact of the Collateral Channel on Productivity"

Sergi Basco (Universitat de Barcelona)

David Lopez-Rodriguez (Banco de España)

Enrique Moral-Benito (Banco de España)

A Data Appendix

A.1 Data Coverage

Table A.1: Employment, Wage Bill and Firms Coverage 2003-2007

(a) Manufacturing Sector

	Employment	Wage Bill	Firms
Panel Data			
2003-2007	77.7	85.5	84.6
Annual Data			
2003	75.7	86.3	83.2
2004	76.5	86.8	85.2
2005	77.1	85.7	83.1
2006	79.7	85.6	84.5
2007	79.3	82.9	86.9

Note: Each cell corresponds to the coverage, expressed as a percentage with respect to the official census, of full-time equivalent employment, wage-earners remuneration and number of firms, respectively, of the manufacturing sector in the database of the Bank of Spain (BdE) relative to the data publicly reported by the Spanish National Institute of Statistics (INE). The official employment and wage bill data come from the Production and Generation of Income Accounts by Branches of Activity and the data on the number of firms come from DIRCE Census on Business, which are the data reported in Eurostat Structural Business Statistics.

Table A.2: Firm Size Distribution by Employment Categories 2003-2007

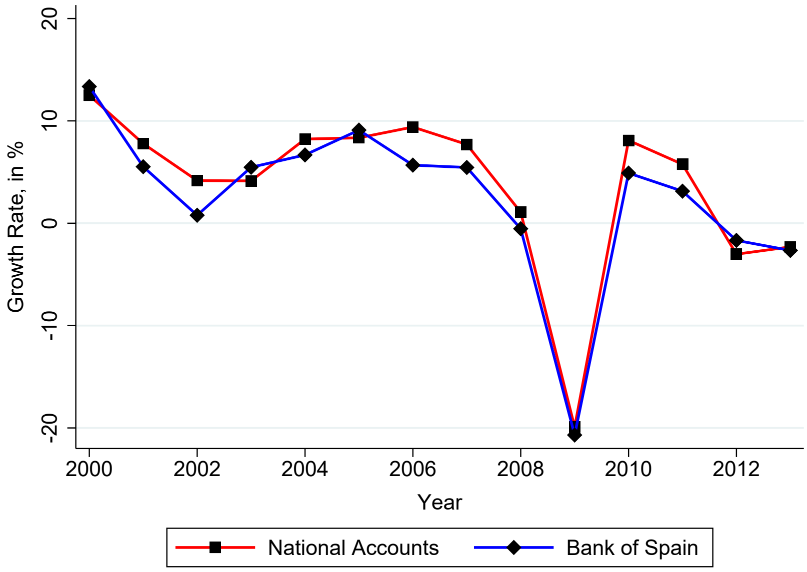
(a) Manufacturing Sector

	0 to 9	10 to 19	20 to 49	50 to 200	> 200
Panel Data					
2003-2007	72.9	88.9	90.7	87.5	93.4
Annual Data					
2003	68.3	85.6	89.4	87.5	92.1
2004	71.8	87.9	91.8	89.0	90.3
2005	74.3	89.1	90.2	83.3	95.2
2006	73.8	91.4	90.5	85.0	94.9
2007	76.3	90.5	91.5	92.7	94.5

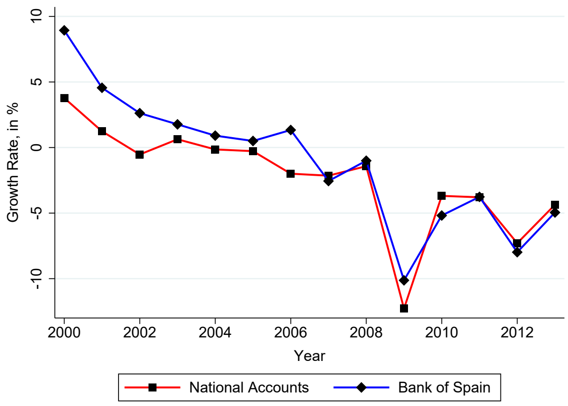
Note: Each cell corresponds to the coverage of the number of firms by employment size category, expressed as a percentage with respect to the official census of firms of that size category, of the manufacturing sector in the database of the Bank of Spain (BdE) relative to the data publicly reported by the Spanish National Institute of Statistics (INE). The official data on the number of firms come from the DIRCE Census on Business, which are the data reported in Eurostat Structural Business Statistics.

Figure A.1: Manufacturing Sector Dynamics

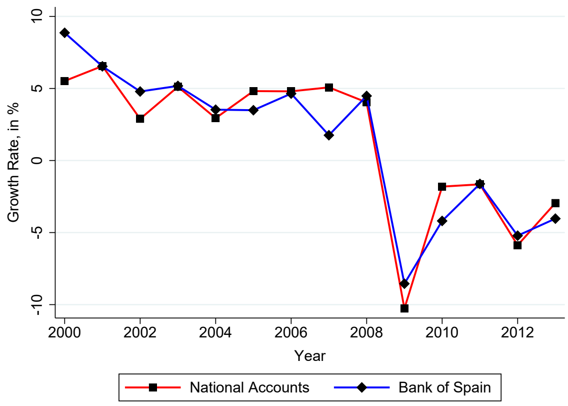
(a) Output Dynamics



(b) Employment Dynamics



(c) Wage Bill Dynamics

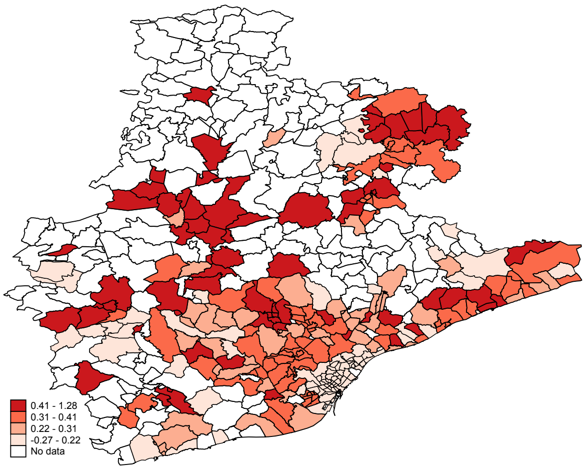


Note: Figures compare the average annual growth rates of the Bank of Spain (BdE) firm-level dataset with respect to the annual aggregate growth rates in the Production and Generation of Income Accounts by Branches of Activity in the National Accounts relative to a) production; b) full-time equivalent employment of wage earners; and c) wage-earners remuneration, in the manufacturing sector between 2000 and 2013. The micro-aggregates in the BdE dataset are computed as the sum of firms' reported, respectively, a) net operating revenue; b) average employment; and c) labor expenditures (wages and social security contributions). The correlation rate between the micro and macro aggregates is 0.91 for employment and 0.96 for both production and the wage bill.

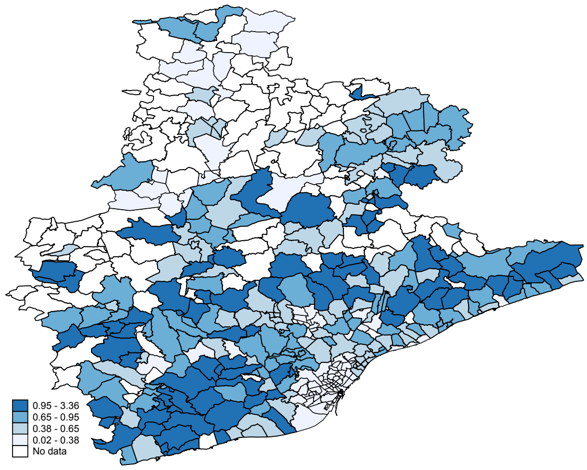
B Appendix Figures

Figure B.1: The House Price Boom in Spain. Variation Across Municipalities

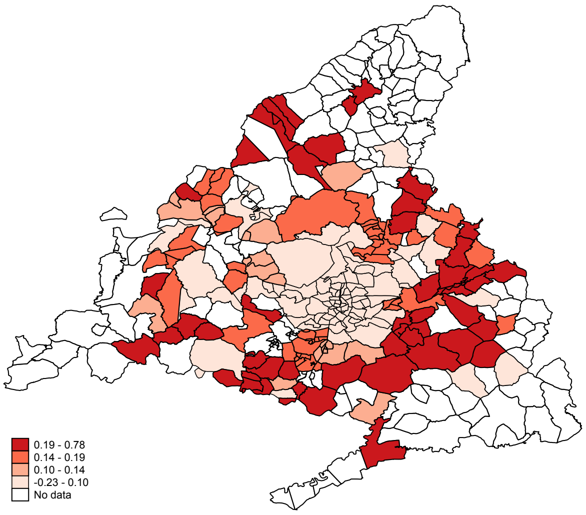
(a) Change in House Prices (Barcelona)



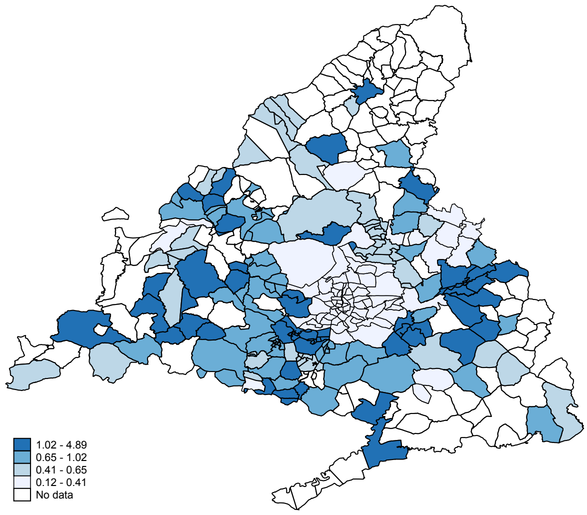
(b) Ratio of Buildable Urban Land (Barcelona)



(c) Change in House Prices (Madrid)



(d) Ratio of Buildable Urban Land (Madrid)

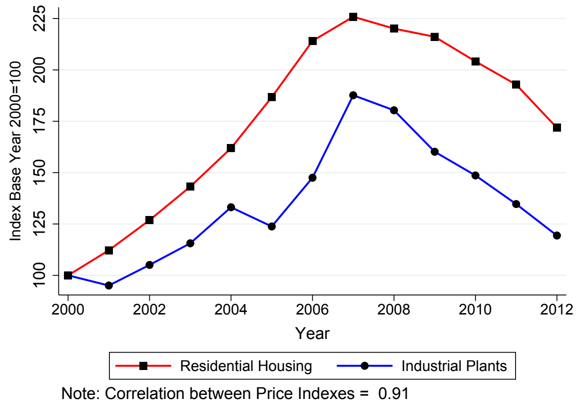


Note: Panels (a) and (c) show the cumulative growth rate from 2003 to 2007 of the average house price index in real terms for the municipalities of the provinces of Barcelona (Panel a) and Madrid (Panel c). Panels (b) and (d) report the Buildable Urban Land Ratio in 1997 for municipalities in the provinces of Barcelona (Panel b) and Madrid (Panel d). The Buildable Urban Land Ratio refers to the ratio between the potential urban land surface and the surface of urban land with structures already built in 1997 for the municipalities included in the sample. The municipality distribution at the province level of the cumulative growth rates of house prices and the urban land ratio is divided into quartiles. Higher house price growth rates are reported with more intense red colors, while greater urban land supply is reflected with more intense blue colors. Municipalities without information appear in white, with the label “No data”.

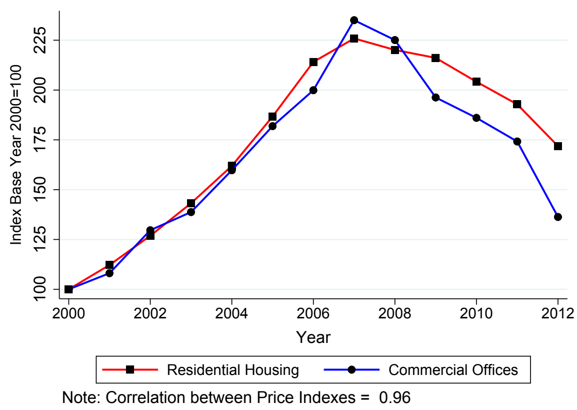
Figure B.2: Residential Prices vs Non-Residential Real Estate Prices

(a) Commercial Buildings

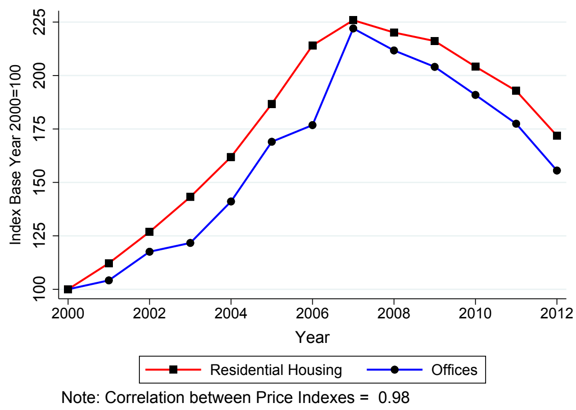
(b) Industrial Plants



(c) Commercial Offices

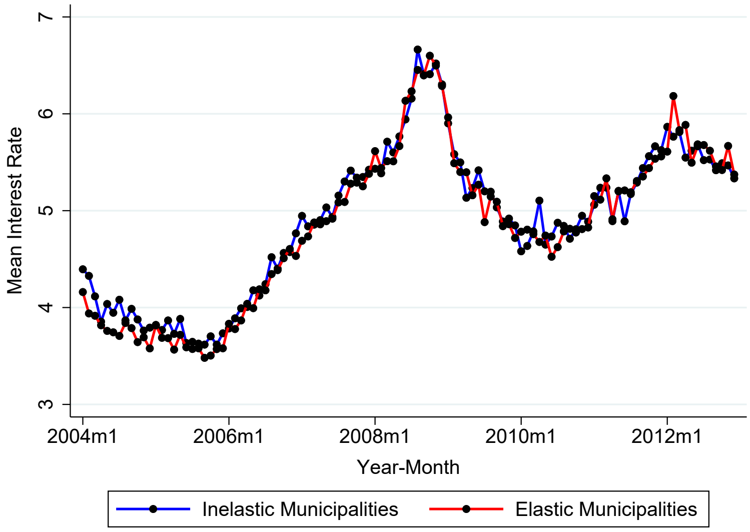


(d) Offices



Note: Figures compare the evolution of the residential house price index in nominal terms for Spain between 2000 and 2012, taking 2000 as the base year, with the dynamics of the non-residential real estate price indices of a) commercial buildings; b) industrial plants; c) commercial offices; and d) offices. Data come from the Spanish Ownership Registry and the Bank of Spain (BdE).

Figure B.3: Interest Rates and Buildable Urban Land Ratio



Note: Figure plots the monthly average initial nominal interest rate of loans with a maturity of more than 1 year granted to firms by the banking sector when the borrowers provides real estate assets as collateral for the loan. The averages are reported for firms located in elastic and inelastic municipalities. Elastic (inelastic) municipalities are those that are above the 75th (below the 25th) percentile in the municipalities' distribution of the ratio of buildable urban land in Spain in 1997. Data come from the Ownership Registry of Spain and the Spanish Cadastre.

C Appendix Tables

C.1 Additional Tables

C.1.1 House Prices and Local Geographical Conditions

Table C.1 shows that the there is a negative cross-sectional correlation between the ratio of buildable urban land (computed for different years) and the growth of house prices across Spanish municipalities during the years of the housing boom (2003-2007).

Table C.1: House Prices and Buildable Urban Land

Dependent variable:	House Prices Cumulative Growth (2003-2007)			
	(1) 1995	(2) 1996	(3) 1997	(4) 1998
Buildable Urban Land Ratio	-0.014***	-0.016**	-0.014**	-0.017**
	(0.005)	(0.006)	(0.006)	(0.007)
Observations	1,653	1,676	1,683	1,665
R-squared	0.122	0.118	0.118	0.119
Province FE	Yes	Yes	Yes	Yes

Note: Standard errors clustered at the municipality level in parenthesis. The dependent variable is the cumulative growth rate of real house prices of residential housing in municipalities with firms included in the estimation sample during the housing boom period (2003-2007). Buildable Urban Land Ratio refers to the ratio between the potential urban land surface and the urban land surface with structures already built in the years 1995, 1996, 1997 and 1998 for the municipalities included in the sample. Significance levels: ***$p<0.01$, **$p<0.05$, *$p<0.1$.

C.1.2 Poisson pseudo-likelihood regression

Table C.2 reports the estimates of running the Poisson pseudo-likelihood (PPML) regression with multiple levels of fixed effects (see, for instance, Gourieoux et al. 1984 or Santos Silva and Tenreyro 2006, 2011). This estimation method provides a natural way to deal with cases in which the dependent variable is non-negative and there are a large number of 0 values, as is the case in our application. The number of observations in these estimates corresponds to the number of firm-years that we observe in our sample when taking into account only those firms that change the defined credit status at least once during the sample period. The qualitative estimates of the PPML model are consistent with the OLS estimates of the linear probability model reported in the main text. Taken together, these results lead us to conclude that we cannot reject that the collateral channel also operated in the extensive margin of credit, but the limitations of these estimation procedures prevent us from making a causal and quantitative interpretation of them.

Table C.2: Extensive Margin of Credit

Dependent variable:	Acceptance of a New Loan Application					
	Acceptance Dummy		Number of Loans		Proportion of Loans	
Δ Ln(House Prices)	-0.201***	-0.128*	-0.173**	-0.072	-0.203**	-0.178**
	(0.066)	(0.068)	(0.073)	(0.075)	(0.086)	(0.087)
Tangibility	0.186**	0.234***	0.121	0.170*	0.429***	0.453***
	(0.077)	(0.079)	(0.087)	(0.087)	(0.099)	(0.100)
Δ Ln(House Prices) × Tangibility	0.531***	0.460**	0.467**	0.411**	0.701***	0.651***
	(0.177)	(0.180)	(0.193)	(0.195)	(0.225)	(0.226)
Observations	69,987	69,739	69,987	69,739	69,987	69,739
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	No	Yes	No	Yes	No	Yes

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have a positive capital stock in the years included in the sample. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The number of observations in these estimates corresponds to the number of firm-years that we observe in our sample when taking into account only those firms that change the defined credit status at least once during the sample period. Columns 1 to 6 report the estimates of running the Poisson pseudo-likelihood (PPML) regression with different sets of fixed effects. The dependent variable in columns 1 and 2 is a dummy that takes value 1 for firm i when a bank accepts at least one new loan application. The dependent variable in columns 3 and 4 is the number of new loan applications from firm i that are accepted by the banks. The dependent variable in columns 5 and 6 is the proportion of new loans over the total number of loans granted by banks to the firm i. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

C.2 Robustness Analysis

In this Appendix we present estimates of our baseline regressions that address various sources of endogeneity that could bias the 2SLS estimates discussed in subsections 5.2. and 5.3. The sensitivity analysis focuses on the preferred specification of equation 4 that includes firm fixed effects and industry-region-year fixed effects. The sensitivity exercises are divided into four broad areas of analysis: i) the examination of potential heterogeneous responses that may be concealed in the average estimates; ii) the inclusion of controls for additional confounding factors; iii) the analysis of specific sources of endogeneity; and iv) additional robustness tests.

C.2.1 Heterogeneous responses

Firm Size

Financial constraints and investment decisions may be related to the size of the firm. In this case, the relevance of the collateral channel in the accumulation of capital can be heterogeneous across firms and the average estimates could hide differential responses between firms with different sizes. We undertake three empirical exercises whose results rule out that our estimates are driven by a specific segment of the demand for capital associated with the size of the firm.

First, we examine the relevance of firm size as an additional confounding factor that may explain investment and credit dynamics over the firm's life cycle. In Tables C.3 and C.4 we report our baseline specifications for investment and credit, respectively, but we add annual measures of log firm size during the housing boom as controls. Log firm size is computed using three alternative measures: average employment (columns 1 and 2), total sales in real terms (columns 3 and 4), and total assets in real terms (columns 5 and 6). As expected, these controls have a significant and positive effect on investment and credit growth, but our OLS and 2SLS estimates are very robust with minor changes in the estimated house price elasticities.

Second, the aggregate relevance of the collateral channel could be reduced when this mechanism is concentrated among the smallest firms. To explore this possibility, we show weighted least square (WLS) estimates of our baseline equations. We weight firms according to the three size measures discussed above, but taking the log of the average firm size (employment, sales and assets) during the housing boom (2003-2007). The estimates reported in Tables C.5 and C.6 indicate that the weighting of observations has a small quantitative impact on the coefficients of interest, discarding the possibility that the average estimates of the collateral channel were driven only by the smallest firms.

Finally, we divide the sample of manufacturing firms into three subsamples based on their size as measured by their average employment during the housing boom. Specifically, we label as small firms those with between 1 and 20 employees; as medium firms the ones between 21 and 49 employees; and as large firms when they have 50 or more employees. The 2SLS estimates reported in Tables C.7 and C.8 indicate a stronger collateral channel in the segment of medium firms which, compared to the average response, exhibits significantly larger house price elasticities for both investment and credit. The 2SLS estimates of the coefficient associated with the interaction term for large firms maintain the positive sign, but do not have statistical significance in the credit equation and its significance is at the 10% level in the investment equation. However, estimates from this small segment of large firms should be considered with caution as the F-tests associated with the first-stage indicate a problem of weak instruments leading to unreliable point estimates in the second-stage.

Table C.3: House Prices and Investment - Firm Size Controls

Dependent variable:	Investment					
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.041**	-0.719**	-0.044***	-0.759**	-0.041***	-0.705**
	(0.016)	(0.307)	(0.016)	(0.299)	(0.015)	(0.287)
Tangibility	0.934***	0.632***	0.956***	0.654***	1.064***	0.773***
	(0.026)	(0.047)	(0.025)	(0.046)	(0.024)	(0.046)
Δ Ln(House Prices) $\times$ Tangibility	0.128***	3.217***	0.133***	3.224***	0.128***	3.102***
	(0.039)	(0.463)	(0.038)	(0.446)	(0.036)	(0.450)
Ln(Employment)	0.019***	0.022***				
	(0.005)	(0.005)				
Ln(Sales)			0.093***	0.095***		
			(0.006)	(0.006)		
Ln(Assets)					0.410***	0.410***
					(0.008)	(0.008)
Observations	175,258	175,258	185,910	185,910	186,452	186,452
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		11.19		10.33		10.33
1st Stage F-Stat. on IV-2		45.69		47.39		47.41

Note: Standard errors clustered at the municipality level in parenthesis. The baseline specification for the investment equation includes annual measures of log firm size during the housing boom as additional controls. The log firm size is computed using three alternative measures: the average employment (columns 1 and 2), total sales in real terms (columns 3 and 4) and total assets in real terms (columns 5 and 6). The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have a positive capital stock in the years included in the sample. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.4: House Prices and Credit - Firm Size Controls

Dependent variable:	Credit					
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.042**	-0.152	-0.045**	-0.191	-0.043**	-0.134
	(0.019)	(0.488)	(0.018)	(0.448)	(0.018)	(0.454)
Tangibility	0.256***	0.090	0.298***	0.138**	0.356***	0.213***
	(0.031)	(0.059)	(0.029)	(0.056)	(0.027)	(0.055)
Δ Ln(House Prices) × Tangibility	0.118**	1.837***	0.126***	1.780***	0.119***	1.599***
	(0.048)	(0.488)	(0.046)	(0.461)	(0.046)	(0.452)
Ln(Employment)	0.052***	0.054***				
	(0.008)	(0.008)				
Ln(Sales)			0.178***	0.180***		
			(0.009)	(0.009)		
Ln(Assets)					0.352***	0.353***
					(0.010)	(0.010)
Observations	149,005	149,005	158,157	158,157	158,432	158,432
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		9.62		8.96		8.99
1st Stage F-Stat. on IV-2		42.26		43.64		43.79

Note: Standard errors clustered at the municipality level in parenthesis. The baseline specification for the credit equation includes annual measures of log firm size during the housing boom as additional controls. The log firm size is computed using three alternative measures: the average employment (columns 1 and 2), total sales in real terms (columns 3 and 4) and total assets in real terms (columns 5 and 6). The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.5: House Prices and Investment - Weighted Least Squares

Dependent variable:	Investment					
Weighting variable:	Ln(Av.Employment)		Ln(Av.Sales)		Ln(Av.Assets)	
	(1) WLS	(2) 2SLS	(3) WLS	(4) 2SLS	(5) WLS	(6) 2SLS
Δ Ln(House Prices)	-0.044***	-0.837***	-0.046***	-0.750**	-0.046***	-0.766***
	(0.016)	(0.295)	(0.016)	(0.297)	(0.015)	(0.295)
Tangibility	0.905***	0.583***	0.928***	0.629***	0.920***	0.619***
	(0.028)	(0.050)	(0.025)	(0.045)	(0.025)	(0.045)
Δ Ln(House Prices) × Tangibility	0.139***	3.450***	0.138***	3.204***	0.137***	3.228***
	(0.040)	(0.496)	(0.038)	(0.445)	(0.038)	(0.445)
Observations	175,158	175,158	186,380	186,380	186,596	186,596
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		9.97		10.05		10.21
1st Stage F-Stat. on IV-2		37.37		45.34		45.42

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have a positive capital stock in the years included in the sample. For any X, $\Delta \text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. We use weighted least squares to estimate the regression parameters and weight firms according to three measures of firm size computed as averages over the housing boom period (2003-2007): i) the log employment; ii) the log of real sales; and ii) the log of total assets in real terms. Columns 1, 3 and 5 report Weighted Least Squares (WLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates using the same weights. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.6: House Prices and Credit - Weighted Least Squares

Dependent variable:	Credit					
Weighting variable:	Ln(Av.Employment)		Ln(Av.Sales)		Ln(Av.Assets)	
	(1) WLS	(2) 2SLS	(3) WLS	(4) 2SLS	(5) WLS	(6) 2SLS
Δ Ln(House Prices)	-0.039*	-0.366	-0.044**	-0.181	-0.045**	-0.198
	(0.021)	(0.550)	(0.019)	(0.479)	(0.019)	(0.474)
Tangibility	0.235***	0.033	0.245***	0.089	0.248***	0.088
	(0.033)	(0.064)	(0.029)	(0.056)	(0.029)	(0.057)
Δ Ln(House Prices) × Tangibility	0.109**	2.198***	0.122**	1.742***	0.120**	1.771***
	(0.053)	(0.542)	(0.048)	(0.465)	(0.048)	(0.469)
Observations	149,841	149,841	158,365	158,365	158,475	158,475
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		8.45		8.62		8.81
1st Stage F-Stat. on IV-2		33.99		41.50		41.63

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. We use weighted least squares to estimate the regression parameters and weight firms according to three measures of firm size computed as averages over the housing boom period (2003-2007): i) the log employment; ii) the log of real sales; and ii) the log of total assets in real terms. Columns 1, 3 and 5 report Weighted Least Squares (WLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates using the same weights. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.7: Investment and Firm Size

Dependent variable:	Investment					
	OLS			2SLS		
	(1) Small	(2) Medium	(3) Large	(4) Small	(5) Medium	(6) Large
Δ Ln(House Prices)	-0.038**	-0.048	-0.089*	-0.784**	-0.145	-1.218*
	(0.017)	(0.035)	(0.053)	(0.329)	(0.746)	(0.720)
Tangibility	0.951***	0.890***	0.620***	0.664***	0.539***	0.438***
	(0.030)	(0.052)	(0.095)	(0.048)	(0.102)	(0.150)
Δ Ln(House Prices) × Tangibility	0.117***	0.156*	0.227	3.022***	4.251***	2.166*
	(0.042)	(0.087)	(0.142)	(0.445)	(1.015)	(1.228)
Observations	136,631	32,278	10,057	136,631	32,278	10,057
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1				10.66	3.21	5.25
1st Stage F-Stat. on IV-2				48.99	32.55	6.28

Note: Standard errors clustered at the municipality level in parenthesis. Firms are divided into three subsamples based on their size as measured by their average employment during the housing boom. Specifically, we label as small firms those with between 1 and 20 employees; as medium firms the ones between 21 and 49 employees; and as large firms when they have 50 or more employees. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have a positive capital stock in the years included in the sample. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 to 3 report Ordinary Least Squares (OLS) estimates, and columns 4 to 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.8: Banking Credit and Firm Size

Dependent variable:	ΔLn(Credit)					
	(1) Small	(2) Medium	(3) Large	(4) Small	(5) Medium	(6) Large
Δ Ln(House Prices)	-0.046**	-0.042	-0.074	0.144	-0.679	-1.864
	(0.021)	(0.042)	(0.099)	(0.511)	(0.994)	(2.034)
Tangibility	0.267***	0.158**	0.141	0.138**	-0.124	0.009
	(0.031)	(0.078)	(0.144)	(0.058)	(0.146)	(0.260)
Δ Ln(House Prices) ×	0.110**	0.150	0.168	1.429***	3.325***	1.894
Tangibility	(0.051)	(0.113)	(0.262)	(0.478)	(1.195)	(2.457)
Observations	112,885	29,974	9,188	112,885	29,974	9,188
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1				9.32	3.11	4.08
1st Stage F-Stat. on IV-2				46.74	30.60	5.63

Note: Standard errors clustered at the municipality level in parenthesis. Firms are divided into three subsamples based on their size as measured by their average employment during the housing boom. Specifically, we label as small firms those with between 1 and 20 employees; as medium firms the ones between 21 and 49 employees; and as large firms when they have 50 or more employees. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 to 3 report Ordinary Least Squares (OLS) estimates, and columns 4 to 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

The main provider of credit

According to influential research on the determinants of the Spanish housing boom (see Fernández-Villaverde, Garicano and Santos, 2013), the mismanagement of politically-oriented saving banks played a prominent role in shaping the buildup and bust of the credit cycle. Specifically, savings banks would have allocated credit to riskier borrowers (households and firms) due to the connection between the dynamics of house prices and the lending capacity of these banks. Thus, a potential concern is that our findings on credit misallocation across firms may be driven by the lending policies of a particular segment of the credit supply, savings banks, which may have allocated credit to a specific group of manufacturing firms. To address this concern, Table C.9 reports OLS and 2SLS estimates on the credit channel, separating our sample of manufacturing firms into two subsamples of firms based on whether their main source of credit comes from commercial banks (columns 1 and 2) or from savings banks (columns 3 and 4). The 2SLS estimates in columns (2) and (4) indicate that in both subsamples the coefficient of the interaction term is positive and statistically significant and, most importantly, it is not statistically different between the two subsamples. These results imply that neither the significance nor the magnitude of credit misallocation within industries stems from a particular lending policy of savings banks in this segment of the credit market.[1]

Table C.9: Credit and Banks

Dependent variable:	ΔLn(Credit)			
	Commercial Banks		Savings Banks	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.046**	-0.138	-0.077**	-0.741
	(0.022)	(0.533)	(0.038)	(0.747)
Tangibility	0.187***	0.025	0.399***	0.228**
	(0.033)	(0.064)	(0.055)	(0.097)
Δ Ln(House Prices) $\times$	0.109*	1.816***	0.197**	1.893**
Tangibility	(0.059)	(0.559)	(0.083)	(0.816)
Observations	108,287	108,287	43,650	43,650
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		6.29		5.33
1st Stage F-Stat. on IV-2		30.17		24.74

Note: Standard errors clustered at the municipality level in parenthesis. Firms are classified into two subsamples based on whether their main source of credit comes from commercial banks or from savings bank. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

C.2.2 Additional confounding factors

One potential concern about the robustness of our main estimates is that there were time-varying firm-level variables that are not constant at the industry-region-year level that could be associated with both investment (or credit) and the tangibility rate of firms, in either positive or negative ways. The existence of these unobserved determinants of investment and credit could also be related to our instrument, thus creating biases in our 2SLS estimates. In this case, not considering these confounding factors in our baseline specification could create an omitted bias that would raise questions about the consistency of our estimates.

[1] This analysis refers to the corporate credit segment within manufacturing industries and, therefore, does not rule out the potential role of savings banks in the salient credit boom in the construction and real estate sectors, as well as in the household mortgage market during the period 2003-2007.

To address these concerns, we added several covariates in our baseline specification to control for additional confounding factors. In particular, we separately included three firm-level covariates: i) the log of the leverage ratio, measured as the ratio between the total outstanding debt and the book value of assets; ii) the log of financial costs, computed as the ratio of financial expenditures over total outstanding debt; and iii) the log productivity of the firm, measured as the estimated TFP-sales adopting the procedure proposed by Levinsohn and Petrin (2003). These covariates measure potential time-varying characteristics that are not captured by firm fixed effects.

Tables C.10 and C.11 report the OLS and 2SLS estimates of the investment and credit equations, respectively, for our preferred specification once we separately include these confounding factors. The estimates show that, conditional on the financial conditions of firms (leverage ratio and financial costs) and productivity shocks, our main results are robust as the relevant coefficient associated with the interaction term remains positive and statistically significant at the 1% level in all specifications.

The coefficients associated with each of the financial covariates (leverage ratio and financial costs) are statistically significant at the 1% level in all specifications. The impact of the leverage ratio on both investment and credit growth rates is positive, indicating a conditional positive correlation between capital accumulation and relative firm indebtedness during the housing boom. The sign of the coefficient associated with financial costs in the investment equation is negative, as would be theoretically expected, since a higher financing cost should be negatively correlated with investment dynamics. Instead, the conditional correlation between financial costs and credit growth is positive, suggesting a higher price (spread) of the banking sector for firms that expand their credit to a greater extent. However, the size of these coefficients is small, indicating a modest contribution of these potential confounding factors in explaining the average dynamics of investment and credit among manufacturing firms.[2]

The introduction of time-variant productivity shocks at the firm-level aims to control for supply determinants of firms' marginal costs that could have an impact on investment decisions and credit allocation by the banking sector. Tables C.10 and C.11 show that the impact of including this control on the point estimates of the coefficients of interest is quantitatively very small, and it has minor impact on the estimates of the average house price elasticities of both investment and credit. In each of these tables, the coefficient associated with the estimated TFP-sales is negative and statistically significant at the 1% level.

[2]These results are consistent with the suggestive evidence on the reduced heterogeneity in the interest rates of new loans granted to firms reported in the Figure B.3 of this Appendix. This figure shows that the banking sector charged average rates similar to corporate loans when the borrower provided real estate assets as collateral, regardless of the geographic characteristics of the municipalities where the real estate assets of these firms were located. As shown in the paper, geographic conditions are a good predictor of local house price dynamics and, thus, this evidence on interest rates suggests that local house price shocks are weakly correlated with the pricing of corporate credit by the banking sector.

Despite the marginal impact on the main estimates of including TFP-sales as a covariate, it is worth noting the significant negative correlation between firm productivity with investment and credit. The sign and size of the productivity coefficient could be viewed as suggestive evidence consistent with a situation in which capital markets would have allocated more capital (e.g., credit) to low-productivity firms that used to have higher tangibility rates. To discard that this potential mechanism can be systematically correlated with the collateral channel, we performed an additional robustness test. We separated the sample into two subsamples of high and low-productivity firms according to their position with respect to the median productivity in the annual distribution of the TFP-sales measure. Tables C.12 and C.13 show that the collateral channel has a causal impact on the relative allocation of capital within each productivity group of firms. For example, among high-productivity firms, those with more real-estate collateral had higher investment rates (and received more credit), discarding that our results were driven by the reallocation of capital towards low-productivity firms with higher tangibility rates.[3]

Finally, firm productivity may be a relevant determinant of the extensive margin of credit. The omission of this potential confounder factor may bias our main estimates. Table C.14 shows the estimates of the linear probability model, using as dependent variables the three measures discussed in section 5.3., when TFP-sales is included as a covariate. The qualitative results are in line with those of the robustness on the intensive margin of credit: i) the coefficient associated with firm productivity is negative and statistically significant at the 1% level; but ii) the impact of including this time-varying covariate in the point estimates of the relevant coefficients associated with the interaction term is very small.

[3] In the sample of manufacturing firms, the average tangibility rate for high-productivity firms is 25.3%, while the average tangibility rate is 32.0% for the subsample of low-productivity firms.

Table C.10: House Prices and Investment - Additional Confounding Factors

Dependent variable:	Investment					
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.046***	-1.041***	-0.044**	-0.977***	-0.046***	-0.740**
	(0.017)	(0.308)	(0.018)	(0.314)	(0.016)	(0.301)
Tangibility	0.958***	0.571***	0.979***	0.600***	0.904***	0.608***
	(0.027)	(0.057)	(0.029)	(0.059)	(0.024)	(0.045)
Δ Ln(House Prices) ×	0.135***	4.025***	0.123***	3.907***	0.136***	3.174***
Tangibility	(0.041)	(0.571)	(0.043)	(0.582)	(0.038)	(0.438)
Ln(Leverage Ratio)	0.032***	0.040***				
	(0.003)	(0.003)				
Ln(Financial Costs)			-0.044***	-0.047***		
			(0.003)	(0.003)		
Ln(TFP)					-0.180***	-0.183***
					(0.017)	(0.018)
Observations	174,022	174,022	162,100	162,100	186,357	186,357
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		9.86		9.70		10.31
1st Stage F-Stat. on IV-2		40.95		36.88		47.26

Note: Standard errors clustered at the municipality level in parenthesis. The baseline specification for the investment equation includes, separately, three additional firm-level covariates: i) the log of the leverage ratio, measured as the ratio between the total outstanding debt and the book value of assets (columns 1 and 2); ii) the log of financial costs, computed as the ratio of financial expenditures over total outstanding debt (columns 3 and 4); and iii) the log productivity of the firm, measured as the estimated TFP-sales adopting the procedure proposed by Levinsohn and Petrin (2003) (columns 5 and 6). The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have a positive capital stock in the years included in the sample. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.11: House Prices and Credit - Additional Confounding Factors

Dependent variable:	Credit					
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.059***	-0.682*	-0.055***	-0.422	-0.044**	-0.173
	(0.018)	(0.411)	(0.019)	(0.402)	(0.018)	(0.457)
Tangibility	0.239***	-0.001	0.233***	0.047	0.237***	0.083
	(0.030)	(0.063)	(0.031)	(0.063)	(0.029)	(0.056)
Δ Ln(House Prices) $\times$ Tangibility	0.155***	2.592***	0.134***	2.002***	0.123***	1.718***
	(0.046)	(0.530)	(0.046)	(0.525)	(0.047)	(0.462)
Ln (Leverage Ratio)	0.056***	0.062***				
	(0.005)	(0.005)				
Ln(Financial Costs)			0.028***	0.027***		
			(0.004)	(0.004)		
Ln(TFP)					-0.083***	-0.085***
					(0.023)	(0.023)
Observations	149,197	149,197	143,614	143,614	158,307	158,307
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		9.18		8.85		9.03
1st Stage F-Stat. on IV-2		40.84		37.71		43.57

Note: Standard errors clustered at the municipality level in parenthesis. The baseline specification for the investment equation includes, separately, three additional firm-level covariates: i) the log of the leverage ratio, measured as the ratio between the total outstanding debt and the book value of assets (columns 1 and 2); ii) the log of financial costs, computed as the ratio of financial expenditures over total outstanding debt (columns 3 and 4); and iii) the log productivity of the firm, measured as the estimated TFP-sales adopting the procedure proposed by Levinsohn and Petrin (2003) (columns 5 and 6). The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.12: Investment and Productivity

Dependent variable:	Investment			
Sample:	High Productivity		Low Productivity	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.039*	-0.282	-0.039*	-1.048***
	(0.021)	(0.463)	(0.021)	(0.402)
Tangibility	0.999***	0.780***	0.882***	0.588***
	(0.035)	(0.059)	(0.035)	(0.062)
Δ Ln(House Prices) × Tangibility	0.161***	2.356***	0.088*	3.175***
	(0.056)	(0.517)	(0.047)	(0.587)
Observations	83,726	83,726	83,860	83,860
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		5.54		10.24
1st Stage F-Stat. on IV-2		48.19		30.26

Note: Standard errors clustered at the municipality level in parenthesis. Firms are classified into two subsamples of high and low-productivity firms according to their position with respect to the median productivity in the annual distribution of the estimated TFP-sales, computed according to the procedure proposed by Levinsohn and Petrin (2003). The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have a positive capital stock in the years included in the sample. For any X, $\Delta \text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.13: Credit and Productivity

Dependent variable:	ΔLn(Credit)			
Sample:	High Productivity		Low Productivity	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.027	-0.264	-0.060*	-0.358
	(0.029)	(0.862)	(0.031)	(0.467)
Tangibility	0.281***	0.155*	0.212***	0.049
	(0.048)	(0.079)	(0.043)	(0.078)
Δ Ln(House Prices) × Tangibility	0.051	1.300**	0.162**	1.907***
	(0.083)	(0.626)	(0.072)	(0.663)
Observations	70,537	70,537	71,564	71,564
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		3.94		10.10
1st Stage F-Stat. on IV-2		48.46		27.46

Note: Standard errors clustered at the municipality level in parenthesis. Firms are classified into two subsamples of high and low-productivity firms according to their position with respect to the median productivity in the annual distribution of the estimated TFP-sales, computed according to the procedure proposed by Levinsohn and Petrin (2003). The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.14: Extensive Margin of Credit and Productivity

Dependent variable:	Acceptance of a New Loan Application					
Sample:	Acceptance Dummy		Number of Loans		Proportion of Loans	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.018	-0.210	-0.010	-0.122	-0.008*	-0.151
	(0.012)	(0.268)	(0.016)	(0.374)	(0.005)	(0.104)
Tangibility	0.039***	0.021	0.038*	-0.029	0.024***	0.007
	(0.015)	(0.027)	(0.021)	(0.040)	(0.007)	(0.011)
Δ Ln(House Prices) $\times$ Tangibility	0.063*	0.244	0.063	0.754**	0.031**	0.203**
	(0.032)	(0.224)	(0.041)	(0.346)	(0.013)	(0.092)
Log TFP-Sales	-0.031***	-0.032***	-0.030*	-0.031*	-0.015***	-0.015***
	(0.012)	(0.012)	(0.017)	(0.017)	(0.005)	(0.005)
Observations	186,357	186,357	186,357	186,357	186,357	186,357
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		10.31		10.31		10.31
1st Stage F-Stat. on IV-2		47.26		47.26		47.26

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available; and iii) they have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable in columns 1 and 2 is a dummy that takes value 1 for firm i when a bank accepts at least one new loan application. The dependent variable in columns 3 and 4 is the number of new loan applications from firm i that are accepted by the banks. The dependent variable in columns 5 and 6 is the proportion of new loans over the total number of loans granted by banks to the firm i. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. The covariate that controls for the log productivity of the firm is measured as the estimated TFP-sales, adopting the procedure proposed by Levinsohn and Petrin (2003). Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

C.2.3 Other sources of endogeneity

Endogeneity of the tangibility rate

The decision to acquire real estate assets is not random and the endogeneity of this decision can bias our main estimates if the tangibility rate of firms' assets were related to the investment prospects of firms and their credit demand. For instance, if firms anticipate that the accumulation of real estate assets will ease their financial constraints, firms may decide to change the composition of their assets by increasing their tangibility to facilitate the allocation of banking credit and, therefore, expand their investment capacity. In this case, firms that own a higher proportion of tangible fixed assets could be more responsive to local demand shocks, biasing the estimates of the coefficient β_3 upwards.

To address this potential source of bias, we adapt the empirical approach followed by Chaney, Sraer and Thesmar (2012) to consider the endogeneity created by the real estate ownership decision. In the first place, we examine the potential role of the value of total assets as a predictor of the tangibility rate of firms in the years prior to the housing boom. Table C.15 reports estimates of a cross-sectional regression of the firms' tangibility rate in 2002 on five quintiles of the log valuation of their total assets in 2002, as well as industry-region fixed effects. Considering that the estimation sample is restricted to manufacturing firms that have information on the volume of total assets for the year 2002, the estimates show that the initial level of total assets is a good predictor of the tangibility rate of firms in the pre-housing boom period. Larger firms, when size is measured in terms of asset value, have lower tangibility rates.

Given the results of Table C.15, we expand our baseline regression by adding controls for initial firm characteristics (initial log asset value quintiles) interacted with the log change in house prices. This empirical procedure aims to control for observed predictors of the tangibility decision, and it allow us to identify the collateral channel when these predictors also make firms more sensitive to changes in house prices.[4] Table C.16 shows that our main results are robust to the inclusion of the observed predictors of firms' initial tangibility rate interacted with changes in local house prices. The OLS and 2SLS estimates of the coefficients of interest are significant at the 1% level, and the investment and credit house prices elasticities are of a similar magnitude to those reported in our baseline specifications in Tables 3 and 4.

[4] This empirical approach to examine the endogeneity of the tangibility decision is justified by the fact, stressed in Chaney, Sraer and Thesmar (2012), that it is hard to find instruments that predict firms' real estate ownership and, thus, the tangibility rate of firms.

Table C.15: Predictors of the Tangibility Rate

Dependent variable:	Tangibility Rate (1) 2002
2nd Quintile Ln(Assets 2002)	-0.003
	(0.003)
3rd Quintile Ln(Assets 2002)	-0.001
	(0.004)
4th Quintile Ln(Assets 2002)	-0.011***
	(0.003)
5th Quintile Ln(Assets 2002)	-0.014***
	(0.004)
Observations	55,457
Industry-Region FE	Yes

Note: Standard errors clustered at the municipality level in parenthesis. The dependent variable is the tangibility rate in 2002 computed as the ratio of tangible fixed assets to total assets. Firms have an identifier that corresponds to their location in one of the five quintiles of the distribution of the log valuation of their total assets in 2002. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.16: Endogeneity of Tangibility Rate

Dependent variable:	Investment		ΔLn(Credit)	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.029	-0.587	-0.021	0.568
	(0.024)	(0.393)	(0.032)	(0.590)
Tangibility	0.941***	0.616***	0.261***	0.104*
	(0.028)	(0.047)	(0.032)	(0.060)
Δ Ln(House Prices) ×	0.133***	3.511***	0.130**	1.822***
Tangibility	(0.039)	(0.482)	(0.053)	(0.501)
2nd Quantile Ln(Assets 2002) ×	-0.014	-0.377*	-0.020	-0.659**
Δ Ln(House Prices)	(0.026)	(0.227)	(0.039)	(0.318)
3rd Quantile Ln(Assets 2002) ×	0.008	-0.582***	-0.035	-0.930***
Δ Ln(House Prices)	(0.025)	(0.222)	(0.036)	(0.304)
4th Quantile Ln(Assets 2002) ×	-0.020	-0.578***	-0.029	-1.132***
Δ Ln(House Prices)	(0.024)	(0.215)	(0.038)	(0.342)
5th Quantile Ln(Assets 2002) ×	-0.031	-0.743***	-0.032	-1.340***
Δ Ln(House Prices)	(0.021)	(0.223)	(0.036)	(0.351)
Observations	157,202	157,202	135,402	135,402
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		13.55		11.58
1st Stage F-Stat. on IV-2		55.72		56.86

Note: Standard errors clustered at the municipality level in parenthesis. The baseline specification for the investment and credit equations adds controls for initial characteristics of the firm (an identifier that corresponds to the location of the firm in one of the five quintiles of the distribution of the log valuation of firm's total assets in 2002) interacted with the log change in house prices. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; and ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available. In columns 1 and 2 the estimation sample includes manufacturing firms that have a positive capital stock; and in columns 3 and 4 includes firms that have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable in columns 1 and 2 is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. The dependent variable in columns 3 and 4 is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Firm size and the municipality dimension

The geographic location of large firms in certain areas may raise concerns of reverse causality that could bias our estimates. For instance, the economic activity and house prices of a small municipality can be greatly affected by the investment decisions of large firms. This fact would affect the consistency of our 2SLS estimates if the capital accumulation of these firms were the one driving the house price dynamics in these municipalities. To address this potential source of bias, we restrict our sample to small and medium-sized firms (defined in terms of average annual employment and computed as the mean of this measure for the housing boom period) located in municipalities that exceed certain population thresholds in the pre-boom year 2002. Tables C.17 and C.18 report OLS and 2SLS estimates for investment and credit equations for firms with less than 50 employees located in municipalities whose population exceeds, respectively, a) 5,000 inhabitants; b) 10,000 inhabitants; and c) 50,000 inhabitants. The estimates of our main parameter of interest, β_3, and the house price elasticities are robust to these sampling restrictions. Thus, this result suggests that firms do not have the capacity to affect the dynamics of local house prices with their input decisions. The estimated coefficients of the interaction term between the change in house prices and the tangibility rate remain economically and statistically significant at the 1% level. The only exception is the 2SLS estimate of the relevant coefficient in the credit equation (column 6 in Table C.18) where, although the size of the coefficient is close to the baseline estimate, the increase in standard errors makes the coefficient statistically significant at the 10% level.

Table C.17: House Prices and Investment - Small and Medium Firms and Big Municipalities

Dependent variable:	Investment					
Sample of firms:	Small and Medium Firms					
Sample of municipalities:	>5.000 inhabitants		>10.000 inhabitants		>50.000 inhabitants	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.063***	-0.494	-0.082***	-0.886**	-0.165***	-0.209
	(0.022)	(0.383)	(0.028)	(0.404)	(0.047)	(3.177)
Tangibility	0.940***	0.670***	0.935***	0.678***	0.854***	0.649***
	(0.030)	(0.046)	(0.034)	(0.048)	(0.052)	(0.069)
Δ Ln(House Prices) ×	0.175***	3.028***	0.218***	2.968***	0.491***	2.889***
Tangibility	(0.055)	(0.445)	(0.073)	(0.455)	(0.142)	(0.671)
Observations	147,129	147,129	125,489	125,489	64,262	64,262
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		9.13		5.89		0.15
1st Stage F-Stat. on IV-2		61.94		56.89		20.00

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) have average employment during the housing boom below 50 employees; and ii) they are located in municipalities whose population in 2002 exceeds, respectively, a) 5,000 inhabitants; b) 10,000 inhabitants; and c) 50,000 inhabitants. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.18: House Prices and Credit - Small and Medium Firms and Big Municipalities

Dependent variable:	Credit					
Sample of firms:	Small and Medium Firms					
Sample of municipalities:	>5.000 inhabitants		>10.000 inhabitants		>50.000 inhabitants	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS	(5) OLS	(6) 2SLS
Δ Ln(House Prices)	-0.057**	-0.025	-0.054**	-0.268	-0.150***	3.551
	(0.022)	(0.500)	(0.026)	(0.483)	(0.049)	(14.463)
Tangibility	0.241***	0.098	0.239***	0.113*	0.183***	0.114
	(0.033)	(0.061)	(0.036)	(0.061)	(0.051)	(0.189)
Δ Ln(House Prices) × Tangibility	0.165***	1.713***	0.170**	1.549***	0.400***	1.621*
	(0.061)	(0.496)	(0.071)	(0.485)	(0.129)	(0.920)
Observations	124,216	124,216	105,557	105,557	52,937	52,937
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		8.51		6.06		0.09
1st Stage F-Stat. on IV-2		61.87		60.82		23.68

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) have average employment during the housing boom below 50 employees; and ii) they are located in municipalities whose population in 2002 exceeds, respectively, a) 5,000 inhabitants; b) 10,000 inhabitants; and c) 50,000 inhabitants. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Tangibility refers to the proportion of the book value of physical property (real estate, factory, and equipment) owned by a firm over the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1, 3 and 5 report Ordinary Least Squares (OLS) estimates, and columns 2, 4 and 6 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

C.2.4 Additional robustness tests

Investment as the change in the capital-labor ratio

We estimate our main specification on the investment equation by now considering the log change in the capital-labor ratio as the dependent variable. The estimates reported in Table C.19 are qualitatively similar to those reported in the main text in which the log difference of the capital stock was used as the dependent variable (Table 3). Specifically, consistent with the theoretical predictions of the model, the coefficient of the interaction term is positive and statistically significant at 1% in all specifications. Using the 2SLS estimates to compute the house price elasticity for the capital-labor ratio, the dispersion of this measure, as a function of the tangibility rate, is similar to the elasticity of the capital stock. For instance, given the same local house price shock, the capital-labor ratio would increase by 92pp for firms moving from the bottom 25th percentile of the distribution of tangible fixed assets to the 75th percentile of this distribution. These estimates point to an increasing dispersion of the capital-labor ratio associated with local house price shocks and, therefore, they can be considered as further evidence on the impact of the collateral channel on the misallocation of capital.

Table C.19: House Prices and Capital-Labor Ratio

Dependent variable:	ΔLn(Capital/Wage Bill)					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ Ln(House Prices)	-0.028*	-0.030*	-0.033*	-0.854***	-0.864***	-0.953***
	(0.017)	(0.017)	(0.017)	(0.245)	(0.255)	(0.318)
Tangibility	1.000***	0.999***	1.000***	0.766***	0.739***	0.719***
	(0.028)	(0.029)	(0.029)	(0.044)	(0.046)	(0.047)
Δ Ln(House Prices) $\times$	0.092**	0.097**	0.102**	2.472***	2.741***	2.966***
Tangibility	(0.042)	(0.042)	(0.042)	(0.410)	(0.430)	(0.447)
Observations	186,526	186,526	186,478	186,526	186,526	186,478
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Industry-Year FE	No	Yes	No	No	Yes	No
Industry-Region-Year FE	No	No	Yes	No	No	Yes
1st Stage F-Stat. on IV-1				16.35	16.02	10.41
1st Stage F-Stat. on IV-2				45.88	45.57	47.26

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes firms in the non-financial market economy, excluding the construction and the real estate sectors, that i) are active in at least one year in the period 2003-2007; ii) are located in municipalities where both residential house price indices and measures of pre-boom housing supply elasticites are available; and iii) have positive stock of capital in the years included in the sample. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. Dependent variable is the firm's yearly investment rate that is measured by the log difference of the stock of capital over the wage bill between years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in municipality m and year t. Tangibility refers to the proportion of the book value on physical property (real estate, factories and equipment) owned by a firm over the book value of its total assets in year t as reported in firm's balance sheet. Columns 1 to 3 report Ordinary Least Squares (OLS) estimates, and columns 4 to 6 report Two-Stage Least Squares (2SLS) estimates. F-statitics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Excluding from the sample subsidiaries of multinational groups

Table C.20 excludes from our baseline sample of manufacturing firms the subsidiaries of foreign multinationals that operate in Spain. This can be justified because the investment and credit decisions of these firms could react to specific local demand shocks differently from the decisions of domestic companies and, also, because the decisions of the subsidiaries could be related to the unobserved collateral value of the multinational group. The results show that the OLS and 2SLS estimates of the impact of house prices on both investment and credit are not significantly affected by the exclusion of these firms, which only represent 5% of the estimation sample.

Table C.20: Robustness: sample of domestic manufacturing firms

Sample:	Excluding subsidiaries of multinationals			
Dependent variable:	Investment		Credit	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.042***	-0.810***	-0.040**	-0.336
	(0.016)	(0.295)	(0.019)	(0.404)
Tangibility	0.922***	0.626***	0.249***	0.090
	(0.027)	(0.046)	(0.030)	(0.056)
Δ Ln(House Prices) × Tangibility	0.128***	3.153***	0.120**	1.762***
	(0.038)	(0.443)	(0.048)	(0.459)
Observations	177,246	177,246	150,536	150,536
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		9.82		8.52
1st Stage F-Stat. on IV-2		45.61		42.01

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample of manufacturing firms excludes the subsidiaries of foreign multinationals operating in Spain. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. Dependent variable in columns 1 and 2 is the firm's yearly investment rate that is measured by the log difference of the stock of capital between years $t-1$ and t measured in real terms. Dependent variable in columns 3 and 4 is the yearly growth rate of firm's credit defined the log difference of firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in municipality m and year t. Tangibility refers to the proportion of the book value on physical property (real estate, factories and equipment) owned by a firm over the book value of its total assets in year t as reported in firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. F-statitics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Clustering of standard errors at different levels

In Table C.21 we depart from our baseline level of clustering (municipality) and show our baseline OLS and 2SLS estimates for investment and credit for our preferred specification with i) province clustering; ii) two-way clustering by province and industry; and iii) two-way clustering by municipality and industry. Focusing on the coefficient of the interaction term, related to the main prediction of the model, the standard errors are somewhat larger when we use province clustering, and very similar or smaller when we use two-way clustering by province and industry and two-way clustering by municipality and industry. In all cases, the coefficient of interest remains statistically significant at the 1% level.

Table C.21: Robustness to different levels of clustering

Dependent variable:	Investment		Credit	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.045	-0.760	-0.045	-0.185
Clustering: province	(0.018)	(0.272)	(0.014)	(0.409)
Clustering: prov. and ind.	(0.012)	(0.254)	(0.014)	(0.313)
Clustering: mun. and ind.	(0.011)	(0.282)	(0.016)	(0.353)
Tangibility	0.929	0.631	0.248	0.094
Clustering: province	(0.050)	(0.043)	(0.029)	(0.056)
Clustering: prov. and ind.	(0.063)	(0.064)	(0.042)	(0.054)
Clustering: mun. and ind.	(0.055)	(0.066)	(0.042)	(0.055)
Δ Ln(House Prices) $\times$ Tangibility	0.134	3.181	0.123	1.711
Clustering: province	(0.046)	(0.504)	(0.040)	(0.543)
Clustering: prov. and ind.	(0.034)	(0.373)	(0.033)	(0.379)
Clustering: mun. and ind.	(0.029)	(0.319)	(0.034)	(0.313)
Observations	186,602	186,602	158,477	158,477
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes

Note: For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. Dependent variable in columns 1 and 2 is the firm's yearly investment rate that is measured by the log difference of the stock of capital between years $t-1$ and t measured in real terms. Dependent variable in columns 3 and 4 is the yearly growth rate of firm's credit defined the log difference of firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in municipality m and year t. Tangibility refers to the proportion of the book value on physical property (real estate, factories and equipment) owned by a firm over the book value of its total assets in year t as reported in firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. The significance level of the coefficient of the interaction term is under 1% for all the specifications when clustering standard errors at different levels.

Non-Financial Market Economy

Lastly, we report the main estimates for the investment and credit equations considering all firms active in the non-financial market economy. The non-financial market economy includes all sectors of activity excluding those related to public sector activity (e.g., health, education, public security or administration), mining industries and financial activity (e.g., banking or insurance activities). We also exclude firms in the construction and real estate sectors from the sample. The main results on the investment and credit estimates reported below in Tables C.22 and C.23 are qualitatively robust when these industries are included, suggesting that our main finding on the impact of the collateral channel as a mechanism that generates capital misallocation within industries applies to the whole non-financial market economy.[5]

Table C.22: House Prices and Investment in the Non-Financial Market Economy

Dependent variable:	Investment					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ Ln(House Prices)	-0.036***	-0.037***	-0.039***	-0.478***	-0.581***	-0.619***
	(0.011)	(0.011)	(0.011)	(0.172)	(0.187)	(0.202)
Tangibility	0.968***	0.970***	0.972***	0.768***	0.725***	0.727***
	(0.020)	(0.021)	(0.021)	(0.025)	(0.029)	(0.029)
Δ Ln(House Prices) ×	0.110***	0.113***	0.112***	2.207***	2.709***	2.695***
Tangibility	(0.030)	(0.032)	(0.032)	(0.238)	(0.290)	(0.285)
Observations	662,563	662,563	662,388	662,563	662,563	662,388
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Industry-Year FE	No	Yes	No	No	Yes	No
Industry-Region-Year FE	No	No	Yes	No	No	Yes
1st Stage F-Stat. on IV-1				12.86	14.78	11.35
1st Stage F-Stat. on IV-2				59.55	56.84	57.31

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes firms in the non-financial market economy, excluding the construction and the real estate sectors, that i) are active in at least one year in the period 2003-2007; ii) are located in municipalities where both residential house price indices and measures of pre-boom housing supply elasticites are available; and iii) have positive stock of capital in the years included in the sample. For any X, $\Delta \text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. Dependent variable is the firm's yearly investment rate that is measured by the log difference of the stock of capital between years $t-1$ and t measured in real terms. House prices denote the average price index in real terms of residential housing in municipality m and year t. Tangibility refers to the proportion of the book value on physical property (real estate, factories and equipment) owned by a firm over the book value of its total assets in year t as reported in firm's balance sheet. Columns 1 to 3 report Ordinary Least Squares (OLS) estimates, and columns 4 to 6 report Two-Stage Least Squares (2SLS) estimates. F-statitics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

[5] See Almunia, Lopez-Rodriguez and Moral-Benito (2018) for details on the process of cleaning and building the database, as well as an exhaustive analysis of the representativeness of this micro dataset with respect to the official statistics of the Spanish economy.

Table C.23: House Prices and Banking Credit

Dependent variable:	ΔLn(Credit)					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Δ Ln(House Prices)	-0.020*	-0.019	-0.023**	0.181	0.191	0.100
	(0.012)	(0.012)	(0.011)	(0.318)	(0.322)	(0.319)
Tangibility	0.283***	0.283***	0.286***	0.175***	0.173***	0.183***
	(0.019)	(0.019)	(0.019)	(0.029)	(0.030)	(0.031)
Δ Ln(House Prices) ×	0.062*	0.057*	0.058*	1.234***	1.256***	1.146***
Tangibility	(0.032)	(0.032)	(0.031)	(0.233)	(0.252)	(0.243)
Observations	524,320	524,320	524,140	524,320	524,320	524,140
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	Yes	No	No
Industry-Year FE	No	Yes	No	No	Yes	No
Industry-Region-Year FE	No	No	Yes	No	No	Yes
1st Stage F-Stat. on IV-1				10.77	12.43	9.55
1st Stage F-Stat. on IV-2				57.58	54.26	55.99

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes firms in the non-financial market economy, excluding the construction and the real estate sectors, that i) are active in at least one year in the period 2003-2007; ii) are located in municipalities where both residential house price indices and measures of pre-boom housing supply elasticites are available; and iii) have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. Dependent variable is the yearly growth rate of firm's credit defined the log difference of firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in municipality m and year t. Tangibility refers to the proportion of the book value on physical property (real estate, factories and equipment) owned by a firm over the book value of its total assets in year t as reported in firm's balance sheet. Columns 1 to 3 report Ordinary Least Squares (OLS) estimates, and columns 4 to 6 report Two-Stage Least Squares (2SLS) estimates. F-statitics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Measurement of the real-estate collateral

Data limitations prevent us from having an accurate measure of firms' real estate collateral because this information is not reported in the financial statements submitted to the Commercial Registry by the Spanish firms. As argued in the discussion on measurement issues included in subsection 4.3., we assume that heterogeneous local changes in house prices are the main source of variation of our proxy of real estate collateral, i.e., firm's tangibility rate. When this presumption holds, in the context of our empirical model that includes multiple fixed effects (firm fixed effects but also industry-location-time fixed effects), our empirical strategy allows us to identify the collateral channel, mitigating the potential biases created by using the firm's tangibility rate as a measure of real estate collateral.

In this subsection we examine the robustness of our results by computing an alternative measure of real estate collateral for the set of firms for which we have more information on the different components of their tangible fixed assets. This information is provided to us by the Statistics Department of the Bank of Spain, which has collected and processed the microdata of the firms that submitted more detailed information in their financial statements to the Commercial Registry. The obligation to submit more detailed balance sheet information is restricted to the largest firms[6], thus, composition effects and sampling selection issues have to be taken into account when conducting these empirical analyses.

Extended data on firm assets is only available for 4,5% (2,8%) of manufacturing (market economy) firms in the estimation sample and, as expected, these firms are among the largest firms that were active between 2003 and 2007. For example, in the manufacturing sample of firms that submit a non-simplified balance sheet, the average employment is 70 employees compared to 16 employees in the total sample, and average assets (sales) in real terms stands at 12.2 (13.8) millions euros, which contrasts with the 1.9 (2.1) million euros for the complete sample. In the case of the market economy, there is also a significant bias towards largest companies in the restricted sample since the average employment is 47 employees compared to 11 employees in the total sample, and average assets (sales) in real terms stands at 7.7 (11.1) millions euros, which contrasts with the 1.2 (1.6) million euros for the complete sample.

Using the available detailed data on assets for the largest firms, we compute an alternative proxy for real estate collateral using information on the gross book value of land and buildings owned by firms. In particular, we calculate the ratio of gross real estate assets to net total assets as the main proxy to undertake robustness analysis. This proxy does not provide a precise measure of net real estate collateral because we do not have data on accumulated depreciation

[6]According to the accounting rules introduced in 1990, firms were allowed to submit the simplified balance sheet when in a given year at least two of the following circumstances occurred: i) the average number of employees is not greater than 50; ii) total assets do not exceed 230 million pesetas (equivalent to 1.38 million euros); and iii) total sales are less than 480 million pesetas (equivalent to 2.88 million euros). The nominal thresholds were periodically updated in order to take into account the effect of inflation.

of real estate assets. Indeed, this proxy implicitly assumes that real estate assets have not been depreciated and, thus, these assets contribute less to the dynamics of capital depreciation than equipment. The latter could be justified by Spanish accounting legislation, which in that period applied a low depreciation rate for real estate assets (50 years as a general rule) compared to faster depreciation of equipment goods (between 4 and 7 years).[7]

We compute simple summary statistics for the sample of firms in the market economy for which we can calculate different measures of real estate collateral and its components. This descriptive evidence indicates that the average tangibility rate for this sample of firms is 0.22, lower than the average of 0.28 in the estimation sample that includes all firms. This tangibility rate drops to 0.12 for the set of firms whose gross value of land and buildings is 0, while the rate for firms with positive gross real estate collateral reaches a value of 0.27, closer to the sample mean in the estimation sample. Among the firms that own real estate assets, this component represents on average more than 60% of the gross book value of tangible fixed assets, with the rest of the gross value of these assets corresponding to equipment.

Having in mind the methodological limitations discussed above, we run our baseline equations for investment and credit using our alternative proxy for the real estate collateral of firms. Table C.24 reports the OLS and 2SLS estimates of our preferred specification for investment (columns 1 and 2) and credit (columns 3 and 4) for the sample of manufacturing firms. The 2SLS results for the manufacturing sample indicate that the relevant coefficients associated with the interaction term are positive but they are not statistically significant in the presence of large standard errors. The relative small estimation sample and a problem of weak instruments, revealed by the low F-tests associated with the first-stage of the estimation procedure, point to unreliable estimates that should be viewed with caution. Table C.25 shows estimates for a larger sample of firms in the non-financial market economy. In this case, there is not a weak instruments problem in the first-stage, which provides greater reliability to our second-stage estimates. The 2SLS estimates of the interaction term are positive and significant at the 5% level for the investment equation and at 10% level for the credit one. These estimates can be seen as a robustness test of our results when we use alternative measures of real estate collateral, although they should be evaluated with carefulness given the data limitations to calculate an accurate measure of net real estate collateral and the sample biases towards the largest firms.

In addition to this robustness, we perform a variance decomposition exercise for the subsample of large firms for which we can proxy their relative composition of tangible fixed assets between real estate and equipment assets. To undertake this exercise, we consider observations for which neither the tangibility rate nor its two components are equal to zero. The compu-

[7] As an alternative proxy, we calculated a measure of gross real estate collateral as the ratio of the gross book value of real estate to the gross value of total assets. This alternative measure implicitly assumes that the total depreciation of assets is distributed proportionally among different items within fixed assets. The results of the empirical exercises that use this alternative measure of gross real estate collateral are qualitatively the same as those discussed below.

tation consists of decomposing the share of the explained variance (R^2) of an OLS model into contributions of groups of regressor variables using Shapley values. This exercise indicates that the gross book value of land and buildings contributes in the range of 65% to 75% to the share of the explained variance of an OLS model that regress the tangibility rate on our proxy of real estate collateral, a relative measure of gross equipment assets and multiple fixed effects as specified in our baseline regression. This contribution reaches 60% of the variation in the smallest subsample for manufacturing industries. These results show that among the largest firms, which on average have a lower relative weight of tangible fixed assets, the land and buildings component explains most of the variation in the collateral proxy used in our regressions (i.e., the tangibility rate).

Table C.24: Measurement of Real Estate Collateral

Manufacturing Sector

Sample:	Manufacturing Sector			
Dependent variable:	Investment		ΔLn(Credit)	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.032	-0.870	-0.068	-0.562
	(0.044)	(1.285)	(0.081)	(1.650)
Real Estate Collateral	0.148	-0.080	0.130	-0.005
	(0.190)	(0.325)	(0.264)	(0.497)
Δ Ln(House Prices) $\times$ Real Estate Collateral	0.039	1.737	0.007	0.977
	(0.245)	(2.147)	(0.471)	(3.524)
Observations	8,552	8,552	6,300	6,300
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		1.72		3.82
1st Stage F-Stat. on IV-2		4.24		8.65

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes manufacturing firms that i) are active for at least one year in the period 2003-2007; and ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available. In columns 1 and 2 the estimation sample includes manufacturing firms that have a positive capital stock; and in columns 3 and 4 includes firms that have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable in columns 1 and 2 is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. The dependent variable in columns 3 and 4 is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Real estate collateral refers to the ratio between the gross book value of land and buildings owned by a firm and the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

Table C.25: Measurement of Real Estate Collateral

Non-Financial Market Economy

Sample:	Market Economy			
Dependent variable:	Investment		ΔLn(Credit)	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
Δ Ln(House Prices)	-0.069	0.278	-0.055	0.125
	(0.042)	(0.971)	(0.060)	(1.227)
Real Estate Collateral	0.435***	0.262	0.412**	0.043
	(0.108)	(0.164)	(0.161)	(0.279)
Δ Ln(House Prices) $\times$ Real Estate Collateral	0.270	2.378**	0.197	4.390*
	(0.193)	(1.096)	(0.295)	(2.478)
Observations	18,817	18,817	17,258	17,258
Firm FE	Yes	Yes	Yes	Yes
Industry-Region-Year FE	Yes	Yes	Yes	Yes
1st Stage F-Stat. on IV-1		3.08		2.91
1st Stage F-Stat. on IV-2		30.08		24.62

Note: Standard errors clustered at the municipality level in parenthesis. The estimation sample includes firms that i) are active for at least one year in the period 2003-2007; and ii) they are located in municipalities where residential house price indices and measures of housing supply elasticities are available. In columns 1 and 2 the estimation sample includes manufacturing firms that have a positive capital stock; and in columns 3 and 4 includes firms that have outstanding debt with the banking sector. For any X, $\Delta\text{Ln}(X)$ is the log difference in X between year $t-1$ and year t for the period 2003-2007. The dependent variable in columns 1 and 2 is the annual investment rate of the firm that is measured by the log difference of the capital stock between the years $t-1$ and t measured in real terms. The dependent variable in columns 3 and 4 is the annual growth rate of the firm's credit defined as the log difference of the firm's outstanding credit with the banking system in real terms. House prices denote the average price index in real terms of residential housing in the municipality m and the year t. Real estate collateral refers to the ratio between the gross book value of land and buildings owned by a firm and the book value of its total assets in year t as reported on the firm's balance sheet. Columns 1 and 3 report Ordinary Least Squares (OLS) estimates, and columns 2 and 4 report Two-Stage Least Squares (2SLS) estimates. F-statistics denote the Sanderson-Windmeijer (SW) weak identification tests in the presence of multiple endogenous regressors. F-statistic on IV-1 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $HSE_m * \Delta R_t$ equals zero. F-statistic on IV-2 denotes the corresponding test statistic for the null hypothesis that the first-stage coefficient on $Tang_{imt} * (HSE_m * \Delta R_t)$ equals zero. Significance levels: ***p<0.01, **p<0.05, *p<0.1.

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