The collateral channel:

Heterogeneity within and between countries*

Jérôme Héricourt, Jean Imbs and Lise Patureau†

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Abstract

We explore the implications of firm-level heterogeneity for the response of investment to financial shocks, both at the micro and aggregate levels. We estimate the response of investment to local real-estate prices, instrumented to capture exogenous changes in financial constraints, in the universe of French firms over 1994-2015. We characterize the distribution of these responses across firms and find the estimates fall with firm size and productivity. We then ascribe these estimates to the values of firm size and productivity observed in other UE countries, in order to characterize the heterogeneity of the collateral channel there. The heterogeneity in firm distributions across countries translates into heterogeneous distributions of the collateral channel both within and across UE countries, mostly for firms below the median of the size/performance distribution. Last, we make use of these distributions to recover the aggregate sensitivity of investment to the real estate value. Despite the heterogeneity in the collateral channel distributions across UE countries, they do not display much heterogeneity in the aggregate collateral channel.

JEL classification: D31, E25, E44, G01

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†Corresponding author: Jérôme Héricourt, Université Paris-Saclay - Université d'Évry, CEPS-EPEE, CEPII, and CEPREMAP; Email: jerome.hericourt@univ-evry.fr. Jean Imbs: New York University Abu Dhabi, PSE, and CEPR; Email: jmi5@nyu.edu. Lise Patureau: University Paris Dauphine - PSL University, LEDa; Email: lise.patureau@dauphine.psl.eu.

1 Introduction

With imperfect financial markets, firms' access to external finance is limited by the value of collateral assets (Barro, 1976, Stiglitz and Weiss, 1981, Hart and Moore, 1994). Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) described the macroeconomic implications of such imperfections: By deteriorating the value of collateral assets recessions increase financial constraints and depress investment further hence output, leading to a "financial accelerator" mechanism.

This collateral channel is likely to be heterogeneous across firms: Provided that financing constraints fall with firm performance, so should the firm investment's response to a shock on its collateral value. Beyond the micro implication, such an heterogeneity is also important for the magnitude of the aggregate collateral channel at country level. For example, different firm size distributions have different implications for the sensitivity of aggregate investment to collateral shocks if they have different dispersions, even if they have the same mean. In other words, cross-country differences in firm size distributions may translate into different values for the aggregate collateral channel across countries. In fact, firm-level data provide a straightforward way to obtain estimates of the sensitivity of aggregate investment to financing constrinats across countries from the bottom up.

In this paper, we start with a firm-level estimation of the response of investment to changes in collateral value, which we exploit to obtain estimates of the intensity of the collateral channel at different points in the firm size distribution. The estimation is performed in French data and its results are exploited in other countries where we observe firm size distribution, but not anything else. Using this bottom-up approach makes it possible to get a sense of the distribution of the sensitivity of investment to the collateral value at micro level for other countries, and ultimately an estimate of the aggregate collateral channel there.

There are several hurdles to cross before we can achieve this objective. Firstly we need firm-level information on investment and real estate assets. These are readily available for listed companies and used for instance in Chaney et al. (2012). But listed companies are probably least affected by financial constraints and so those data would provide a lower bound to the sensitivity of investment to real estate, at best. Here we use the universe of French firm-level data for the period 1994-2015 combined with local real-estate prices gathered by the French notaries. Secondly, there are evident issues of simultaneity and endogeneity between investment and real estate cycles. We follow Chaney et al. (2012) and compute an instrumental variable for local real estate prices based on the interaction between housing loan interest rates and local supply elasticity. Thirdly, we take full account of concerns reported, e. g. by Welch (2021), and test various alternative specifications to make sure there does exist a relationship between the value of real-estate holdings and investment.

Fourthly, in order to transcribe to other countries the investment sensitivity values estimated on French data for segments of the size distribution there, we need cross-country information on the distribution of firms. We resort to the CompNet data that compile information on the distributions of firm size and productivity for the main European economies.[1]. Of course, the French estimates are only transferable to other countries inasmuch as these countries display comparable financial systems: Collateral values may be less relevant in countries where more external financing is done through financial markets, rather than banks. Therefore, we focus on seven European countries (Belgium, Denmark, Italy, Netherlands, Portugal, Spain, and Sweden) with financial systems that are comparable to France, especially as regards the importance of bank finance. Finally, we need weights to average bin-level elasticity estimates up to an aggregate accelerator value. We collect these weights from CompNet under the assumption that the distribution of capital assets is a good approximation for the distribution of real estate assets.

Our results are as follows. The sensitivity of investment to changes in local real estate prices for the average French firm is around 0.2. As expected the estimates vary enormously with firm size or productivity: the elasticity ranges between 0.3 and 0.5 below the median firm but it is between 0.07 and 0.2 for the top 10 percent firms, depending on the variable measuring the firm size distribution. These results are robust to different measures of size (including turnover, real value added and labor productivity). They hold in a variety of sub-samples and do not depend on the inclusion of a battery of controls, including fixed effects. These results confirm that collateral values matter much less for large, productive firms than for small ones. And it suggests that focusing on listed firms only minimizes the measured extent of the collateral channel.

Besides, we highlight substantial cross-country heterogeneity in elasticity estimates, which can be ascribed to differences in firm distributions. Given substantial cross-country dispersion in firm labor productivity distribution, the sensitivity of investment is particularly widespread at the lowest deciles of the distribution: It hence ranges from 0.45 in Belgium and 0.5 in the Netherlands to 0.7 in Portugal and in Denmark at the bottom decile of labor productivity. Conversely, heterogeneity is more limited in the top decile, with estimates between 0.18 and 0.26 on our sample of countries.

Yet, this important cross-country heterogeneity does not translate into sizeable differences in aggregate collateral channels across countries, with aggregate values around 0.21 in most studied countries, the Portugal being a notable exception with an aggregate elasticity of 0.25. This explains through the dominant share of the more productive firms in total assets, as the investment sensitivity displays few variability across countries at the deciles of the distribution. This is also consistent with the disproportionate weight of big firms in aggregate dynamics emphasized by

[1] The Competitiveness Research Network (CompNet) has been founded by the EU System of Central Banks in 2012. See http://www.comp-net.org/data/

a flourishing literature (among many others, Carvalho and Grassi, 2019, Gabaix, 2011). This result has important implications in terms of policy recommendations. While the aggregate effects of collateral shocks may not substantially differ across EU countries, they have marked heterogenous effects across firms within each EU country. Accordingly, the economic effects of financial shocks should rather be a concern for national authorities than at the centralized (i.e, European Central Bank level).

Our work directly relates to a few recent papers providing empirical, firm-level illustrations of the collateral channel, such as Chaney et al. (2012) on a sample of listed US firms, and Fougere et al. (2019), on a larger French database, but still focusing on big firms. Both find that firm-level investment is sensitive to (real-estate) collateral value, with a semi-elasticity on average equal to 0.06-0.07. Very similar evidence (semi-elasticity of 0.05) are found by Bahaj et al. (2020) based on UK, micro data. In addition, Fougere et al. (2019) find evidence of heterogeneous effects of real estate prices on investment along the sectoral distribution of real estate holdings. Banerjee and Blickle (2021) find that borrowing, investment, and employment are strongly correlated with house price growth in small and young firms based on a firm-level sample spanning six European economies. Building on heterogeneity, Gopinath et al. (2017) quantify how much heterogeneous financing frictions across Spanish firms contribute to sectoral misallocation. Grjebine et al. (2023) find real estate chocks are an important driver of productivity divergence between European countries because of the search for collateral creates misallocation. Catherine et al. (2022) show collateral constraints induce aggregate output losses of 7.1 percent because of misallocation. We contribute to the existing literature at two levels. We first examine the heterogenous responses of investment in the universe of all French firms, including many very small ones. Second, we transcribe the French results to other countries based on the firm size distributions there and propose the first micro-based estimates of the importance of collateral channel across EU countries.

The next section details our empirical methodology and our identification strategy. Section 3 presents the various involved datasets. Section 4 reports our baseline results for France and a number of robustness checks, and section 5 discusses the extension and outcomes for selected EU countries. The last section concludes.

2 Empirical Strategy

2.1 Baseline Model and Methodological Issues

Building on the well-know literature studying the impact of financial constraints on firms' investment behavior (among others, Bond and Meghir, 1994, Gilchrist and Himmelberg, 1998, Love, 2003), Chaney et al. (2009) or Catherine et al. (2022) propose a simple model of investment under collateral constraint delivering the following reduced form expression for firm-level investment

$$INV_{isc,t} = \rho \, RE\ Value_{isc,t} + \beta \, P_{c,t} + \varepsilon_{isc,t} \tag{1}$$

where

$$\begin{aligned} INV_{isc,t} &= \frac{TI_{isc,t}}{K_{isc,t-1}}, \\ RE\ Value_{isc,t} &= \frac{P_{c,t} \, RE\ Value_{isc,t0}}{K_{isc,t-1}}, \end{aligned} \tag{2}$$

where $TI_{isc,t}$ is tangible investment by firm i in sector s, location c, and at time t, $K_{isc,t}$ is firm i's stock of tangible assets or "Property, Plant, and Equipment" (PPE for short), $RE\ Value_{isc,t0}$ is the value of real estate held by firm i at year 0, the year of acquisition for their holdings declared the first year of entry in the database. With $P_{c,t}$ the price of real estate in location c at time t, $P_{c,t}RE\ Value_{isc,t0}$ hence represents the market value at time t_0 of real estate holdings of the firm in location s (i.e, the first year of entry in the database), and $RE\ Value_{isc,t}$ this value normalized by the firm's lagged stock of tangible assets.

In the model, ρ directly maps with the degree of financial constraints in that it appears as a composite measure of the fraction of firms in the sample that face financing constraints, the severity of these financing constraints, and the fraction of real estate that can be used as collateral (see Chaney et al. (2009) for a theoretical modeling of investment decision under collateral constraint). Equation (1) follows Chaney et al. (2012). The value of real estate held by firm i is allowed to vary with its (local) prices only. With quantities held fixed at their initial value, changes in $RE\ Value$ come from fluctuations in real estate asset prices and ρ traces their effects on firm-level investment for those firms that actually hold real estate assets their first year in the sample. Identification comes from the comparison of investment by firms holding real estate versus those that do not. Of course, cycles in asset prices $P_{c,t}$ correlate with investment for other reasons, too, regardless whether a firm holds real estate assets or not. So Equation (1) includes a direct control for real estate prices, whose effect is captured by β.

Endogeneity. As it stands, Equation (1) suffers from various omitted variables biases. We therefore include a battery of fixed effects meant to absorb aggregate (location-year)-level, and firm-level phenomena. Even with these controls, two additional endogeneity issues can still plague the estimation of Equation (1). Firstly, the ownership of real estate assets is not exogenous, even in its initial cross-section. Specifically, one may be worried that real estate prices proxy for local demand shocks, and that land-holding firms are more sensitive to such local demand shocks. This would induce another omitted variable bias in the estimation of ρ. Accordingly, and like Chaney et al. (2012), we introduce additional interaction terms to account for this possibility, involving the quintiles of firms' initial age, initial assets, initial return on assets, and two-digit industry dummies, all interacted with P_{ct}. Equation (1) becomes

$$INV_{isc,t} = \rho\, RE\, Value_{isc,t} + \delta\, CF_{isc,t} + \gamma\, X_{isc,t} + \mu_i + \nu_{ct} + \varepsilon_{isc,t} \tag{3}$$

where μ_i and ν_{ct} are firm- and location-year-fixed effects.[2] Since regressions with more aggregate indicators on the right-hand side could induce a downward bias in the estimation of standard errors (Moulton, 1990), all estimations are also clustered at the location-year level. $X_{isc,t}$ is the vector of additional control variables interacting firm i's age, total assets, return on asset the first year of observation, and two-digit industry dummies with $P_{c,t}$. We show in Table A.12, Appendix D, that these dimensions are good predictors of the real estate value (Column (1)) as well as of the decision to own real estate (Column (2)). This justifies including them in our estimated equation. We also follow Chaney et al. (2012) including $CF_{isc,t}$, the firm's cash flow (income before extraordinary items plus depreciation) normalized by $K_{isc,t-1}$. Standard theoretical approaches emphasize cash flow is a prominent empirical determinant of investment, which may be affected by the cycle in asset prices as well.

Another potential endogeneity bias in Equation (1) has to do with reverse causality. For a large enough firm, investment decisions might impact local real estate prices, generating a positive bias in the estimates of ρ. A third issue comes from measurement error, as housing prices constitute an imperfect proxy for the prices of commercial real estate. Both issues can be addressed with adequate instrumentation of $P_{c,t}$. Following Chaney et al. (2012), we instrument local real estate prices with an interaction between the local elasticity of housing supply and the aggregate mortgage interest rate. The intuition is straightforward: Movements in the mortgage rate affect demand for housing, which is satisfied with increased construction in locations where that is technically or geographically possible. So when the supply elasticity is high, changes in $P_{c,t}$ are minimal in response to movements in the mortgage rate. This isolates fluctuations in local real estate prices that are determined by aggregate and geographic factors (Chaney et al., 2012, Fougere et al., 2019). Inasmuch as the supply elasticities are relevant for commercial real estate, it also potentially provides an adequate proxy for commercial real estate price movements. Incorporating all these refinements in Equation (3), the estimation becomes

$$INV_{isc,t} = \rho\, \widehat{RE\, Value}_{isc,t} + \delta\, CF_{isc,t} + \gamma\, \widehat{X}_{isc,t} + \mu_i + \nu_{ct} + \varepsilon_{isc,t}, \tag{4}$$

where

$$\widehat{RE\, Value}_{isc,t} = \frac{\widehat{P}_{c,t}\, RE\, Value_{isc,0}}{K_{isc,t-1}},$$

$\widehat{P}_{c,t}$ is the fitted value of the first stage estimation:

[2] In this case, we remove P_{ct} as an independent explicative variable since it is completely captured by ν_{ct}.

$$P_{c,t} = \kappa \, \eta_c^s \times i_t + \lambda_t + \nu_c + u_{ct}, \tag{5}$$

η_c^s measures the constraints on the availability of constructible land in location c, and i_t is the aggregate mortgage rate. $\widehat{X}_{isc,t}$ denotes the interactions between firm i's age, total assets, and return on asset with $\widehat{P}_{c,t}$.

The Ratio Problem. Equations (1) to (3) raise another, non-trivial statistical concern related to the use of ratios for the dependent variable as well as some regressors. According to Bartlett and Partnoy (2020), a ratio as dependent variable can generate an omitted variable and measurement error bias. Besides, Welch (2021) support additional issues arising from scaling both dependent ($INV_{isc,t}$) and independent variables (e.g, our main variable of interest $RE\ Value_{isc,t}$ using the same denominator (i.e, the lagged capital stock). Namely, in a fixed-effect estimation, volatility and trends in the denominator can induce spurious associations between variables, here real-estate value and investment.

We implement several strategies to account for these various, potential caveats. Firstly, we add to our baseline specification $1/K_{isc,t-1}$. Suggested by both Bartlett and Partnoy (2020) and Chaney et al. (2020), this inclusion should capture some of the spurious correlation pointed by Welch (2021) and omitted variable bias pointed by Bartlett and Partnoy (2020).[3] Therefore, we estimate:

$$INV_{isc,t} = \rho \, RE\ Value_{isc,t} + \delta \, CF_{isc,t} + \gamma \, X_{isc,t} + \beta \, \frac{1}{K_{isc,t-1}} + \mu_i + \nu_{ct} + \varepsilon_{isc,t} \tag{6}$$

and its IV counterpart:

$$INV_{isc,t} = \rho \, \widehat{RE\ Value}_{isc,t} + \delta \, CF_{isc,t} + \gamma \, \widehat{X}_{isc,t} + \beta \, \frac{1}{K_{isc,t-1}} + \mu_i + \nu_{ct} + \varepsilon_{isc,t}, \tag{7}$$

To further address concerns related to the use of ratio variables and common denominators on the left- and right-hand-side variables, we implement several robustness checks designed to shut down the potential spurious correlation, by removing the time-varying scale factor on the value of real estate. First, as in Chaney et al. (2012), we report estimates based on an alternate version of Equation (6), where $RE\ Value_{isc,t}$ is replaced by an interaction between $P_{c,t}$ and a dummy variable equal to 1 when the firm owns real estate at t_0, 0 otherwise. Second, we present in section 4 additional estimates based on other, alternative measures for real-estate holdings. We start by substituting to our main regressor the inverse hyperbolic sine of the value of real

[3] A strict implementation of Bartlett and Partnoy's (2020) would imply including, together with $RE\ Value_{isc,t}$ and $1/K_{isc,t-1}$, $P_{c,t}\ RE\ Value_{isc,0}$, i.e. the numerator of $RE\ Value_{isc,t}$. However, in contrast with their approach, our parameter of interest is genuinely tied to the scaled (by the capital stock) right-hand side variable, RE value. We have no interest in the unscaled RE Value.

estate holdings in euros (i.e., $log(P_{c,t}\ RE\ Value_{isc,0} + \sqrt{1 + (P_{c,t}\ RE\ Value_{isc,0})^2})$, following again Chaney et al. (2020). We also implement an estimation based on $log(1 + X)$, where X represents the values in euros for investment in tangible assets (dependent variable) and again of real estate holdings. Alternatively, we use as scale variable for the real estate holdings $\frac{1}{K_{isc,t0}}$, that is, the inverse of the stock tangible capital owned by the firm the first year of entry in the database.

2.2 Exploring Heterogeneity

Heterogeneity in France A key contribution of the paper is to document the heterogeneous reaction of firms' investment to changes in collateral value. The underlying idea is that small and less productive firms tend to have more difficult access to external finance (Asdrubali et al., 2022, Beck et al., 2005, Driver and Muñoz-Bugarin, 2019) so that the value of their collateral matters more. First, we exploit the richness of our firm-level database to quantify the extent of heterogeneity in France. To do so, we estimate a modified version of Equation (6), based on a full set of non-parametric interaction terms between the real estate value of the firm ($RE\ Value_{isc,t}$) and a dummy variable indicating where she stands in the distribution of a given performance variable (specifically, labor productivity or value-added). The estimated equation then becomes:

$$INV_{isc,t} = \sum_{j=1}^{n} \rho^j\ RE\ Value_{isc,t} \times Z^j_{isc,0} + \delta\ CF_{isc,t} + \gamma\ X_{isc,t} + \mu_i + \nu_{ct} + \varepsilon_{isc,t}, \quad (8)$$

where $j = \{1, ...n\}$ denotes the set of bins associated with the tested performance variable and $Z^j_{isc,0} = \{0, 1\}$ a dummy indicating if the firm i (in location c and sector s) belongs to the j^{th} bin based on its position in the distribution of performance variable considered Z. To prevail any endogeneity concern, we take the firm's position in the distribution the first year of observation (the first year the firm appears in our dataset). Specifically, we discretize the firms distribution into deciles ($n = 10$).[4] Through this equation, we explore the extent to which financial constraints vary depending on the relative performance of the firms, with the performance being measured through labor productivity, value-added or turnover (See Section 3 for more details).

Exploiting our firm-level database enables us to quantify how much a shock on the collateral may vary depending on the firm' relative performance. In contrast to Fougere et al. (2019), which investigate heterogeneity in the real estate distribution, we put emphasis on another mechanism behind the collateral channel, related to the firm performance. Our intuition is that smaller

[4] The dummy $Z^j_{isc,0}$ takes the value 1 for the category $j = 1$ for a firm whose performance lies below the threshold value estimated at $P10$ the first year of observation, 0 for all $j = 2, ...10$; it takes the value 1 for the category $j = 2$ if the firm' performance lies between the threshold values $P10$ and $P20$ the first year of observation, 0 for the other j categories, and so on.

and/or less productive firms face more severe financial constraints, thereby expecting a larger ρ^j for bins in the lower part of the distribution.

Heterogeneity among European countries Exploring the firm-level heterogeneity dimension brings a second important contribution, that relies on the ability to draw aggregate results from micro-estimates. Specifically, we can make use of the estimates of ρ^j for each specific bin j of the performance variable Z distribution, to compute an aggregate measure of the financial accelerator. The reasoning is the following.

Define the aggregate collateral channel value ρ as the response of (aggregate) investment to changes in the price of collateral, whose proxy here is the average price of real estate assets, as: $\frac{\partial Inv}{\partial RE\ Value}$ with $RE\ Value$ real estate value. From our bottom up approach exploiting firm heterogeneity, we can recast the aggregate value of ρ from the micro-estimates through the following relationship:[5]

$$\frac{\partial Inv}{\partial RE\ Value} = \sum_j \widehat{\rho}_j \omega_j, \tag{9}$$

$$\text{with} \quad \omega_j = \frac{RE_j^{vol}}{RE_T^{vol}} \tag{10}$$

where RE_j^{vol} measures the real estate volume of all firms belonging to the bin j of the performance variable considered, and RE_T^{vol} the corresponding stock at the aggregate level. Otherwise stated, the aggregate value of the collateral channel can be decomposed as the weighted sum of the investment sensitivity by bin of performance, with the appropriate weighting scheme being ω_j the share of real assets holdings of the firms in the j^{th} bin of the performance variable Z considered, in the total stock of real assets holdings.

Relying on this micro-to-macro approach is particularly relevant for quantifying the collateral channel in countries other than France, for which we do not easily dispose of firm-level data, but for which we have sufficient information on the distribution of firms in terms of the performance variable. To fix ideas, say that we consider labor productivity as the performance variable under focus. This is where we make a fruitful use of the Compnet database, from which we extract data on two key dimensions: 1) the thresholds values of labor productivity deciles, by country and year; 2) the distribution of capital stock conditional on the decile of labor productivity, by country and year. From this, we proceed in three steps (see Appendix B.1 for a detailed presentation of the method).

First, once the labor productivity thresholds values have been obtained for each country x considered (using Compnet data taken on average over the period), we plug these country-specific threshold values in our French firm-level data to estimate the sensitivity of investment

[5]More details on the foundations of Equation 9 are reported in Appendix B.1.

by bin using our French firm dataset as "laboratory", based on Equation (8). We hence obtain a set of responses of investment to the collateral shock by bin j and country x, i.e. $\{\widehat{\rho}_j^x\}_{j=1,...,10}$.

Second, we need an estimate for ω_j^x, for each country x. For ω_j^x to be measured, we need to know the real estate volumes conditional for all firms belonging to the bin j of the labor productivity distribution in country x. From the Compnet joint distribution dataset, we can retrieve the distribution of real capital stock conditional on the decile of labor productivity, by country and year. We make use of this information to proxy the distribution ω_j^x (with $j = 10, 20, 30, 40, 50, 60, 70, 80, 90$) for each x European country in the sample (considering the average over the period).

In a third and final step, we combine these two distributions on $\{\widehat{\rho}_j^k\}_{j=1,...,10}$ and $\{\omega_j^k\}_{j=1,...,10}$ to obtain the aggregate response of investment to a collateral shock for each country k, based on Equation (9).

3 Data

3.1 French data

3.1.1 Data sources

Firm-level Data We combine accounting data on an exhaustive sample of French firms, their location, and real estate prices measured at the local level. Accounting data is provided by the French national institute of statistics (INSEE) through several databases: *Bénéfices Réels Normaux* (BRN, 1993-2009), *Fichier complet unifié de Suse* (FICUS, 1994-2007), *Fichier approché des résultats d'Esane* (FARE, 2009-2015) and *Déclaration Annuelle de Données Sociales* (DADS, 1993-2015). The datasets can be merged thanks to a unique firm identifier, called SIREN, which maximises coverage and data availability. The combination of these data sources enables us to collect detailed firm-level information on size, productivity, real estate holdings, a breakdown of asset holdings, and location. The richness of the BRN dataset induces us to mostly rely on this source when available, eventually completing information with those from FICUS (until 2007) and FARE (2009). Firm location is reported in DADS, the number of employees is obtained from BRN and FICUS/FARE, or from DADS when data are missing. All other variables are collected from BRN (or FICUS in case of missing observations) until 2009 then FARE, as BRN, FICUS and FARE provide a large set of variables merging information from the profit and loss account and the balance sheet firms have to declare to the French fiscal administration each year. The dependent variable $INV_{isc,t}$ is obtained from FICUS/FARE as it is missing in BRN, which implies that investment data are missing for 2008 (and the year 2008 consequently excluded from our regressions). Given our normalization with the lagged value of tangible capital stock (property, plant, equipments), we discard the year 1993 from our period of estimation.

As in Chaney et al. (2012) and Fougere et al. (2019), we exclude firms operating in the finance, insurance, real estate, construction, and mining industries. Following Chaney et al. (2012), we also exclude those present for fewer than three consecutive years. The sample thus covers about 705,956 firms per year on average over the full period, which decomposes in about 222,490 firms per year in 1994-2007 (BRN-FICUS-DADS data), and 1,508,075 firms per year over 2009-2014 (including a mix of BRN-FARE-DADS data for 2009, and FARE-DADS data between 2010 and 2014). The much larger number of firms in the FICUS-FARE sub-sample comes from the difference in the firms coverage between these datasets. If FARE provides information on the universe of French firms, BRN is restricted to firms whose sales revenue (pre-tax) is above 763,000 euros.[6] We document the potential differences in firms' characteristics between the two sub-samples later in the descriptive statistics Section 3.1.2. We also check in Table 8 how our baseline results behave on each of these tow subsamples (1994-2007 and 2009-2014).

Local real estate prices are obtained from the French Notary Association ("Notaires de France") and observed at the "strate" level, at yearly frequency over 2000-2014. These data only exist for residential, rather than commercial real estate, for already-built flats and individual houses. Strates are geographic areas where prices are relatively homogeneous as evaluated by Notaries; in areas where a sufficient number of transactions is realized per year (typically, medium to large municipalities), a specific housing price can be calculated. For Paris, the price (for flats) is at the district level (at the municipality level for individual houses). In smaller municipalities, the housing price reported by the Notaries is the one calculated at the department level. Our database provides real estate prices for 283 strates (for flats) and 230 strates (for individual houses), at yearly frequency over 2000-2014, with base year 100 in 2015. We favor housing prices based on flats for its larger coverage.[7] Accordingly, housing prices are either at the district or municipality or department level.[8] They hence constitute an strongly disaggregated snapshot of local real estate prices. As in Chaney et al. (2012), we build real estate prices before 2000 by retropolating housing prices with CPI inflation rates obtained from INSEE over 1949-1999. This allows us to recast the real estate value from the first year of acquisition for all firms with real estate holdings (as detailed later in the section).

Instrumental Variable We adopt the same methodology as in Chaney et al. (2012) or Fougere et al. (2019) to construct the instrument for local housing prices. We combine the housing loan interest rate series provided by the *Banque de France*[9] with the housing supply

[6]Firms below this threshold may still use the BRN option to declare their revenues to the tax administration, but are not constrained to. Therefore, BRN covers in practice much larger firms (in the sense of sales revenues) than FARE, as shown in Table A.3.

[7]We check that our baseline results still hold when real estate prices for individual houses is considered. These results are not reported but available upon request.

[8]Fougere et al. (2019) also observe residential prices, but at the Departement level only.

[9]Thanks are due to Denis Fougère, Rémy Lecat, and Simon Ray for sharing the interest data with us.

elasticity computed by Chapelle and Eyméoud (2018).[10] The housing supply elasticity is measured at the "urban area" level, which does not correspond with the Notaries' "strates". In particular, locations in weakly dense areas are excluded from the urban area coverage.[11] We focus the instrumented estimations on those "strates" that overlap with urban areas. Since not all strates are assigned with an "urban area" identifier, this necessarily reduces the firm coverage. The IV sample thus covers about 230,074 firms per year on average over the full period, which decomposes in about 76,214 firms per year in 1994-2007 (BRN-FICUS data), and 483,577 firms per year over 2009-2014 (FARE data). In this regard, we check how our results behave on each of these two samples in Table 8.

Thanks to the Siren identifier, we are able to observe the real estate asset holdings of each firm in our sample, under the "land, buildings and equipments" entry in their balance sheets. What is of interest for us is the market value of these assets $RE\ Value_{isc,t}$. Yet, real estate is valued at historical cost in accounting data. We recover their market value following the method of Chaney et al. (2012), that can be decomposed in two steps. First, we calculate the age of these assets, as the product of the proportion of these assets claimed as depreciation times their depreciable life, that we estimate of 36 years on average. From this, we recast the year of acquisition of these properties. This methodology requires to discard firms that declare real estate as only land, as land does not depreciate over time (hence, we cannot identify a year of acquisition). This is not likely to alter our results though as firms declaring only land represent 3% (2%) of firms on the full (IV) sample (see Table A.1 in Appendix A.3). Specifically, we determine the age of the real estate assets based on their historical cost reported the first year in the database. Doing so, we eliminate the ulterior purchases of lands and buildings that could be endogenous to investment decisions. Appendix A.2.1 provides more detail on this methodology. Second, we infer the firm's real estate value at any year t over 1994-2014 by inflating their historical costs with local housing prices inflation (from the Notaries database as described above) between the year of acquisition and the current year t. [12]

3.1.2 Descriptive statistics

Table 1 reports some descriptive statistics for some key variables in the French data.

One can notice that the mean real estate value (in normalized terms) is well above the median, which is 0. Even more than 50%, it appears that 70% of firms in our dataset do not own real estate (Table A.1, Appendix A.3). The distribution is highly right-skewed, with

[10]We thank Guillaume Chapelle and Jean-Baptiste Eymeoud for sharing this data with us. See Data Appendix A for more details.

[11]Figure A.2 in Appendix A provides a visual rendition of the resulting geographic coverage.

[12]Denoting $RE\ Value_{isc,t^e}$ the real estate at historical cost declared the first year of entry t^e, we recast the market value of real estate holdings through: $RE\ Value_{isc,t} = \frac{1}{K_{isc,t-1}}\left(\frac{P_{c,t}}{P_{c,t0}} RE\ Value_{isc,t^e}\right)$ with $P_{sc,t0}$ the housing price in location s the year of acquisition $t0$. Alternatively, in the terms of Equation (2), we can write: $RE\ Value_{isc,t} = \frac{1}{K_{isc,t-1}}\left(P_{c,t} RE\ Value_{isc,t0}\right)$ with $RE\ Value_{isc,t0}$ the volume of real estate holdings obtained as the ratio $RE\ Value_{isc,t^e}/P_{c,t0}$.

Table 1: Descriptive statistics: France, Full sample

	Mean	Median	Std	p25	p75
$RE\ Value_{isc,t}$	0.26	0.00	0.54	0.00	0.25
Age	12.84	9.00	13.94	4.00	18.00
Assets	507.38	95.81	1450.89	15.45	377.87
Total sales	731.33	137.51	2665.46	46.06	474.73
$Cash_{isct}$	0.86	0.27	2.54	0.09	0.82
# employees	14.99	5.00	82.88	2.00	12.00
I_{isct}	0.16	0.03	0.41	0.00	0.12
Labor productivity	41.86	29.94	102.56	17.20	49.76
ROA	0.06	0.04	0.19	0.00	0.12
# firms per year	705956.25	236729	725104.75	214764	1,559,134
# years per firm	5.33	5.00	3.84	3	7

Note: The number of firms-year pairs is 2,916,278. Nominal variables are expressed in thousands of euro. $RE\ Value_{isc,t}$ is the ratio of the market value of real estate assets over lagged stock of fixed capital (Property, Plant and Equipment - PPE). Age is the number of years since the firm's inception. $Cash_{isct}$ is defined as income before extraordinary items + depreciation and amortization normalized by lagged PPE. # employees is the number of total employees. I_{isct} is the ratio of tangible investment over lagged PPE. Labor productivity is the ratio of value added over the number of employees. Leverage ratio (fin. debt) is the amount of financial debt divided by total assets. Leverage ratio (total debt) is the amount of total debt divided by total assets. ROA: Return on assets, defined as operational income divided by total assets. The number of years per firm refers to the years in the database.

a limited number of firms holding substantial amounts of assets (the maximum value of real estate value (relative to the lagged capital stock) reaching 5.35). This finding also applies to the distribution of firm size, as measured by total sales, assets, turnover, the number of employees or labor productivity. This stands in line with the literature pointing out the role of large firms in aggregate fluctuations (see Gabaix (2011) as seminal paper). The distribution of investment (normalized by lagged capital stock) is also quite asymmetric, with the mean (0.56) well above the median (0.03) and even above the third quartile of the distribution (0.12). In contrast, if dispersed, the distribution of the return on assets does not display such an asymmetric pattern. These findings suggest to get deeper into the heterogenous link between real estate, investment decisions and firm size and performance.

As a first attempt to characterize different firms behavior depending on the collateral value, Tables A.1 and A.2 and in Appendix A.3 provide the same descriptive statistics as in Table 1, differentiating firms with/without real estate assets. The group of firms with real estate assets tends to contain bigger firms, with higher sales and assets. Yet they are also less productive, less profitable and with lower cash-flows (Table A.2). This is also consistent with the evidence concerning the determinants of real estate ownership reported in Table A.12 (Appendix D): older and larger firms are more likely to be real estate owners, but not the most profitable ones - those located in the last quintile of Return on Assets tend to own *less* real estate. This evidence supports the idea that relatively less performing firms with relatively little internal finance tend to use real estate holdings as collateral. In terms of investment behavior, if the average amount invested is larger for firms with real estate (Table A.1), this is no longer the case once investment is normalized by the capital stock (Table A.2). However, the proportion of firms that invest is higher in the sub-sample of firms with real estate holdings (Table A.1). This suggests some potential differences in the investing behavior along the intensive and the extensive margin that we will investigate when estimating the size of the collateral channel.

As mentioned above, the firms coverage differs between BRN sources (large firms in terms of cash, with pre-tax sales above 763 k€), and FARE sources covering the almost-complete universe of French firms. This raises the question of the comparability of the two samples. In Appendix A.3, we report descriptive statistics distinguishing by data origin BRN of FARE (Table A.3). The difference of firms' characteristics between the two samples justifies that we check the consistency of our elasticity estimates on each sub-sample.

As last investigation, we compare the characteristics of our firms sample on the full vs IV sample. As reported in Table 2, the two samples display similar characteristics, which makes us confident in the consistency of results.

Table 2: Full vs IV Sample

	Mean		Median		Std Dev.	
Sample:	Full	IV	Full	IV	Full	IV
PH_{isct}	0.26	0.22	0.00	0.00	0.54	0.52
Age	12.84	12.31	9.00	8.00	13.94	13.67
Asset	507.38	503.46	95.81	87.86	1450.89	1483.92
Total sales	731.33	741.86	137.51	137.21	2665.46	2756.05
CF_{isct}	0.86	1.00	0.27	0.31	2.54	2.88
Nb of employees	14.99	16.54	5.00	5.00	82.88	107.64
I_{isct}	0.16	0.18	0.03	0.03	0.41	0.43
Labor productivity	41.86	43.38	29.94	30.56	102.56	89.46
ROA	0.06	0.06	0.04	0.04	0.19	0.20
Nb firms-year	2,916,278	1,005,373	2,916,278	1,005,373	0	0
Nb firms/year	1,416,876	451,154	1,658,384	539,395	643,767	208,383

We are interested in the firm distributions of variables Z that are likely to capture the severity of credit constraints: In French data, we obtain estimates of ρ^j for various measures of performance Z, including the number of employees, total assets, real labor productivity, real turnover, real value-added. For these last three variables, we partition our sample of firms on deciles as in Compnet. This gives us a sense of the non-linearities of the collateral constraints depending on the firm performance and size in France.

3.2 EU countries database

3.2.1 Empirical strategy

Our purpose here is to estimate the size and heterogeneity of the collateral channel across EU countries, both at the micro and the aggregate levels. Yet, we do not dispose of such an exhaustive dataset as our French firm dataset for other countries. We palliate this limitation thanks to an original approach that combines individual firm-level data (for France) and a summary of firm distribution in a set of EU countries. For this, we rely on information from the 6^{th} vintage of the CompNet database. Compnet compiles international indicators of firm distribution that build from firm-level data collected by national providers, aggregated and harmonized to allow cross-country comparisons. Various distributions are reported, with information on means, variances, and various percentiles. In that exercise, we only retain real labor productivity as performance variable for our estimation on European countries.[13] Specifically, from CompNet database, we retrieve the thresholds values by bins of real labor productivity for a set of EU countries (Belgium, Denmark, Spain, Italy, Netherlands, Portugal, Sweden). Then we estimate $\widetilde{\rho}_x^j$ on French data, but using the threshold values associated to the jth percentiles of real labor productivity that are specific to each considered country x. This gives us the distribution of the importance of financial constraints along the labor productivity distribution in the various countries considered.

Combining the estimated distribution of $\widetilde{\rho}_x^j$ with adequate proxies for the share ω_x^j for each country x, we can then compute each country's aggregate collateral channel (through Equation (11)). We obtain these proxies from CompNet: ω_x^j measures the share of each percentile j of firms (in terms of labor productivity) in the total stock of real estate assets, for each country x. We assume the distribution of real estate assets is well approximated by the distribution of its tangible assets (real capital), so that ω_x^j can be directly approximated by the observed distributions in CompNet.

For the imputation of French elasticities elsewhere to make sense, we need the nature of credit constraints to be similar across countries, for a given firm size. In particular, we need that (i) financial systems be sufficiently close and (ii) real estate assets be equally acceptable as collateral across the countries of study. Ehrmann et al. (2001) present a comparison of financial systems that conclude European countries are relatively homogeneous in their reliance on bank finance, by contrast with the US. This conclusion aligns with Allen and Gale (2001), who emphasize continental European countries opted for bank-dominated systems. As a result, we focus the imputation of French elasticities onto large and comparable European economies.

Of course, some differences in financial systems exist within the European Union (EU), even more famously within the Euro Area (EA). For example Badarau and Levieuge (2013) document the multi-dimensional differences within the EA as far as banking concentration, bank capitalization, or dependence on banking credit. Badarau-Semenescu and Levieuge (2010) find that the bank lending channel is more prevalent in Germany, Italy, and the Netherlands than in Finland, France, and Spain. Ehrmann et al. (2001) report the percentage of corporate finance done via bank loans in the EU: the ratio was 37.2 percent in France at the end of the

[13] As we develop in Section C, it is not straightforward to compare the values coming from the Compnet database and their equivalent in the French firm data set, for a number of variables in levels (such as value-added or turnover), in part because of normalization issues. Comparing ratios, and especially labor productivity, turns out to be more convincing.

1990s, as against bigger numbers in other large EU economies (Germany, Italy, Spain) and an EU average of 45.2 percent. A decade later, the European Central Bank (2012) highlights an unequal recovery of loans to non-financial corporations following the 2008-2009 financial crisis: In countries going through an EU-IMF adjustment program (Greece, Ireland, and Spain), loan supply had not recovered by 2012 while it had in other EA countries. These statistics suggest that bank lending is an even more important source of external finance in European countries than in France. And therefore that French elasticity estimates are if anything a lower bound of what they are in those countries.

A second condition necessary to impute French elasticities to other countries is that real estate holdings are also used as collateral there. Banerjee and Blickle (2021) investigate the importance of housing as collateral for firm borrowing, investment and employment in six European countries (France, Italy, Portugal, Spain, Sweden, and the UK) between 2004 and 2012. Using firm-level data they find the relationship between regional house price growth and small firm activity is stronger in Sweden, Spain, Portugal, and Italy than in France and the UK, although the differences in estimates are not large. The 2015 ECB Survey on the Access to Finance of Enterprises (SAFE) find that about 80 percent of small companies (with fewer than 50 employees) reported needing collateral in Spain, 60 percent in Italy, and only 44 percent in France. In all these countries, two-thirds of the surveyed firms with fewer than 50 employees reported needing collateral to raise external finance. Half reported using personal assets, including their own house, as collateral. The proportion is 5 percent for large firms, which illustrates the importance of including small, non-listed firms in the analysis. These statistics are suggestive that the need for housing collateral is a recurrent characteristic throughout Europe and that financial frictions in the rest of Europe are slightly more severe than in France.

3.2.2 Descriptive statistics on European data

Heterogeneity of firm performance Table 3 reports the summary of the distribution of real labor productivity for the set of European countries considered, including France, based on the joint distribution series. Notice that the values for France are based on the sample restricted to firms with at least one employee to be consistent with the Compnet database.

We will combine these threshold values with our French firms dataset to get the estimates of $\widehat{\rho}_x^j$ for each country x and quantile j of the performance distribution. To be clear, consider the case for Belgium. We will partition the French firms depending on whether their real labor productivity (the first year in the dataset), lies below 21.41, between 21.4 and 28.7, etc... that correspond to the deciles values observed in Belgium. Running the estimation based on this partition, we will obtain estimates for $\widehat{\rho}_{BEL}^j$, for $j = 1, 2, ...10$. Given that the whole distribution of Belgian firms lies well above that of French firms, we expect lower estimated values for each coefficient $\widehat{\rho}_{BEL}^j$. As a corollary, we expect a lower value of the financial accelerator value at the aggregate level, once these $\widehat{\rho}_{BEL}^j$ have been combined with the appropriate weights ω_{BEL}^j. In

Table 3: Deciles of real labor productivity, European countries

Country	p10	p20	p30	p40	p50	p60	p70	p80	p90
Belgium	21.41	28.68	34.75	40.66	47.13	54.84	65.14	81.38	115.16
Denmark	6.25	10.64	16.40	22.87	28.40	33.60	39.47	47.51	63.68
Italy	9.85	14.28	17.88	21.27	24.77	28.79	33.93	41.83	59.20
Netherlands	15.99	26.19	34.40	42.18	50.47	60.63	74.70	97.43	146.87
Portugal	4.26	7.36	9.77	11.96	14.36	17.29	21.20	27.30	40.30
Spain	9.33	14.19	17.98	21.48	25.16	29.43	34.99	43.43	61.11
Sweden	11.18	18.26	24.04	29.05	34.02	39.78	47.12	58.18	80.32
France Compnet data	15.59	21.90	26.93	31.81	37.13	43.58	52.09	64.71	89.39
France, BFF data	11.50	17.59	22.58	27.5	32.76	38.80	46.38	57.36	78.83

Notes: Authors' computations. Except for the last line, the thresholds values by decile come from the Compnet joint distribution dataset, conditional of the log real labor productivity at the aggregate level. Average values over the period by country. The last line reports our estimates of the real labor productivity thresholds distribution based on the French firms (BFF) datasat restricted to firms with minimum 1 employee, averaged over the period.

contrast, we expect much larger estimates for $\widehat{\rho}^{j}_{PRT}$ and at the aggregate level $\widehat{\rho}_{PRT}$ when running the estimation based on Portugal performance values, as real labor productivity thresholds are systematically lower than in France.

In the last line of Table 3, we also report the threshold values associated to each labor productivity decile obtained on our French firm dataset. If not a perfect match (the thresholds values from Compnet are systematically higher than those obtained on French firm data), the gap is roughly stable over the distribution (higher for Compnet by between 11% and 26% depending on the deciles, but stable for all deciles when taking the absolute difference). This is reassuring as regards the comparability issue of our estimates on French firm data using Compnet threshold values. As the match is not perfect though, we will yet check the consistency between our estimates on French data depending on which threshold values (from Compnet or from the French data set) we use to partition firms.

Weight for aggregation Table 4 reports the relative weights on the EU country sample. Specifically, we calculate the total stock of capital by (log) labor productivity decile by taking the mean value of the capital stock per decile, times the number of firms in the underlying population, for each country-year. The total stock of capital is calculated as the sum over all deciles, on each year of observation. We then take the ratio, that we then average over the whole period.

Table 4: Weight of capital by decile of (log) real labor productivity, European countries

Decile	BEL	DNK	FRA	ITA	NLD	PRT	ESP	SWE
$< p10$	0.023	0.006	0.026	0.030	0.032	0.029	0.035	0.009
$p10 - p20$	0.027	0.012	0.034	0.025	0.043	0.031	0.033	0.010
$p20 - p30$	0.036	0.019	0.048	0.028	0.057	0.033	0.035	0.012
$p30 - p40$	0.046	0.028	0.064	0.032	0.072	0.039	0.042	0.019
$p40 - p50$	0.057	0.042	0.081	0.038	0.091	0.047	0.049	0.019
$p50 - p60$	0.069	0.061	0.099	0.048	0.107	0.062	0.061	0.026
$p60 - p70$	0.082	0.082	0.112	0.063	0.120	0.082	0.077	0.036
$p70 - p80$	0.100	0.104	0.122	0.088	0.115	0.114	0.099	0.102
$p80 - p90$	0.128	0.139	0.140	0.142	0.138	0.165	0.138	0.090
$> p90$	0.431	0.508	0.273	0.506	0.224	0.398	0.432	0.676

Sources: Authors' calculations, based on Compnet 6th version.

4 Collateral Channel in France

4.1 Baseline specification: average effect

Estimation results over the full sample. Table 5 reports the results for the average effect estimation. Columns (1) and (2) report OLS estimates for the complete sample, while columns (3) and (4) show, respectively, OLS and IV results based on data available for the IV estimation. This table follows the progression of our empirical strategy as described in Section 2: column (1) starts with Equation (3), columns (2) and (3) follow with Equation (6), column (4) finishes with Equation (7).

Table 5: Baseline specification

	(1)	(2)	(3)	(4)
Dep. Var		$INV_{isc,t}$		
Estimator	OLS	OLS	OLS	IV
RE Value$_{isc,t}$	0.22^a	0.2^a	0.2^a	0.21^a
	(0.0041)	(0.0039)	(0.0047)	(0.0048)
CF$_{isc,t}$	0.03^a	0.024^a	0.023^a	0.023^a
	(0.00026)	(0.00024)	(0.00031)	(0.0003)
$\frac{1}{K_{isc,t-1}}$		0.63^a	0.63^a	0.63^a
		(0.0085)	(0.0013)	(0.0013)
# Obs.	7998967	7998967	2483951	2483951
Adj. R^2	0.19	0.21	0.21	0.21

Notes: INV = tangible investment normalized by lagged stock of tangible assets K$_{isc,t-1}$. RE Value = market value of real estate holdings normalized by K$_{isc,t-1}$. CF = firm's cash flow normalized by $K_{isc,t-1}$. All estimations include initial controls (ROA, Age, Asset, Industry) × the price of real estate $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. [c], [b], [a] denote, respectively, significance at the 10%, 5%, and 1% levels.

Table 5 support real-estate-holding firm invest more than the others: On average, a 10% increase in the market value of real estate assets translates into a $\simeq 2$ percentage points increase in the investment ratio. Put differently, one additional euro in the value of the average firm's real estate assets translates into a 0.2 euro increase in investment. This estimation is only marginally impacted (columns (1) vs. (2), (3), and (4)) by the introduction of the inverse tangible assets ($\frac{1}{K_{t-1}}$) as a first control for possible spurious correlation induced by the use of a common denominator for left- and right-hand side variables (more on this below) or the use of an instrumental variable strategy. In this regard, column (4) displays the result when the housing price is instrumented with interaction between housing loan interest rates and local housing supply elasticity to account for a potential endogeneity bias.[14] Finally, the main control, $\text{CF}_{isc,t}$, also displays the expected sign: Firms with higher cash ratio invest more than the others.

Our quantification (0.2) of the impact of real-estate holdings on investment is substantially higher than the 0.06 found by Chaney et al. (2012), but their samples restrict to much bigger and much less financially constrained firms than the average firm in our sample, involving many small firms. We explore in more details the implications of this heterogeneity for the collateral channel in Section 4.2. Before, we show our results are unharmed by various alterations of the estimated equation and specific subsamples.

Alternative specifications. As mentioned in Section 2.1, the use of ratios for both the dependent variable and the key right-hand side variable raises non-trivial statistical concerns. We tackle the latter in several ways. First, as in Chaney et al. (2012), we replace our measure of collateral shock $\text{RE Value}_{isc,t}$ by an interaction between real estate prices and a dummy taking the value 1 if the firm owns some real estate assets. Columns (1) to (4) in Table 6 report the results from this specification, on the OLS (columns (1) and (2)) and IV sample (columns (3) and (4). In the latter case, column (3) shows the estimates based on our IV strategy for local prices, while column (4) displays OLS results on the IV sample for comparison purposes. In all cases, the estimated coefficient is positive and strongly significant, indicating that on average, for a unit increase in the local price index, a firm that owns at least some real estate increases its investment rate by 5 to 7 percentage points more than a firm that does not own real estate.

Second, we remove the time variation in the scale factor on the value of real estate, by using as scale variable $\frac{1}{K_{isc,t0}}$, that is, the inverse of the stock tangible capital owned by the firm the first year of entry in the database. Estimates are reported in columns (6) to (8) of Table 6, while column (5) reproduces our preferred estimate for comparison purposes. In columns (7) and (8), we also change the scale factor in CF, for $\frac{1}{K_{isc,t0}}$. Results are qualitatively unchanged: The estimated coefficient on the market value of real estate is positive and strongly significant in columns (6) to (8). The size of the effect is significantly smaller, however: A 10% increase in the market value of real estate assets translates into a $\simeq 0.3$ percentage points increase in the investment ratio. Keep in mind, however, that the standardization with $\frac{1}{K_{isc,t0}}$ creates a

[14]The first-stage results are reported in Table A.13, in Appendix D. They confirm our instrument is a strong predictor for local, housing prices.

downward bias, since it tends to overweight big firms in the estimation - the value of their real estate increases over time, but the value of other tangible assets is frozen to the year of entry in the database. In any case, those results do not question the existence of a positive relationship between real estate holdings and investment.

Table 6: Robustness (1): Ownership dummy & time-invariant scale factor

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. var:	$INV_{isc,t}$							
Main expl. var:	$DumRE_0 \times P_t$				RE Value			
	Full sample		IV sample		Full sample			
$DumRE_0 \times P_t$	0.07^a	0.069^a		0.049^a				
	(0.0031)	(0.0031)		(0.0046)				
$DumRE_0 \times \widehat{P}_t$			0.053^a					
			(0.0044)					
RE $\text{Value}_{isc,t}$					0.2^a			
					(0.0039)			
RE $\text{Value}_{isc,0}$						0.025^a	0.028^a	0.027^a
						(0.00089)	(0.00093)	(0.00091)
$\frac{1}{K_{isc,t-1}}$	0.63^a		0.65^a	0.65^a	0.65^a	0.65^a		0.78^a
	(0.0085)		(0.0088)	(0.013)	(0.013)	(0.0088)		(0.0092)
$\text{CF}_{isc,t}$	0.024^a	0.031^a	0.024^a	0.023^a	0.023^a	0.024^a		
	(0.00024)	(0.00026)	(0.00024)	(0.0003)	(0.0003)	(0.00024)		
$\text{CF}_{isc,0}$							0.00038^a	0.00074^a
							(0.000045)	(0.000075)
# Obs.	7,998,967	7,998,967	2,487,633	2,487,633	7,998,967	7,998,967	7,998,967	7,998,967
Adj. R^2	0.19	0.21	0.21	0.21	0.21	0.21	0.17	0.2

Notes: INV = tangible investment normalized by lagged stock of tangible assets $K_{isc,t-1}$. $DumRE_0 \times P_t$ = dummy variable equal to 1 when the firm owns real estate × the price of real estate $P_{c,t}$. $\widehat{P}_t$ = fitted value for the price of real estate, based on the first-stage regression. RE $\text{Value}_{isc,t}$ = market value of real estate holdings normalized by $K_{isc,t-1}$. RE $\text{Value}_{isc,0}$ = market value of real estate holdings normalized by $K_{isc,0}$. $\text{CF}_{isc,t}$ = firm's cash flow normalized by $K_{isc,t-1}$. $\text{CF}_{isc,0}$ = firm's cash flow normalized by $K_{isc,0}$. All estimations include initial controls (ROA, Age, Asset, Industry) × $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. ^{c}, ^{b}, ^{a} denote, respectively, significance at the 10%, 5%, and 1% levels.

Table 7 reports the results of several additional alterations of our main specification, mainly focused on the definition of the value of real-estate holdings. Columns (1) and (2) use the inverse hyperbolic sine of RE $\text{Value}_{isc,t}$, while columns (3) and (4) rely on the log value of the latter (plus one, to avoid losing firms with no real-estate holdings). In column (5), log-linearization has also been applied to tangible investment on the left-hand side, as well as cash flows and tangible capital stock on the right-hand side. In columns (6) to (8), we go back to ratio variables, but use different time horizons for the numerator and denomination of the real-estate ratio, in the spirit of Welch (2021). In this regard, columns (6) and (7) must be understood as placebos: we do not expect to $INV_{isc,t}$ to react positively to future value of real-estate holdings ($\frac{RE^{val}_{t+1}}{K_t}$ and $\frac{RE^{val}_{t+2}}{K_{t+1}}$).

Overall, Table 7 unambiguously confirms the positive relationship between real-estate value and tangible investment. Columns (1) to (4) show a positive investment response around 0.06: A 10% increase in real-estate holdings produces a 0.6 percentage point rise in the tangible investment ratio. In Column (5), the results from the log-log estimation support a 10% increase in the value of real-estate holdings triggers a 0.3% increase in tangible investment. In columns (6) and (7), future real-estate values (in *t+1* and *t+2*) are *negatively* correlated with investment in the current period, which makes sense: If the firm anticipates some growth of the collateral value in the future, it is rational to delay investment today, since investment will be easier to fund in the future. Conversely, a 10 pp rise in the previous year ratio of real-estate holdings increases the current investment ratio by 0.9 pp (column (8)): a relaxation of financial constraints in the previous year still has positive effects on contemporaneous investment.

Table 7: Robustness (2): Log-transformations and placebos

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.		$INV_{isc,t}$			$log(1+Inv_{isc,t})$		$INV_{isc,t}$	
$asinh(RE_t^{val})$	0.058^a	0.056^a						
	(0.002)	(0.002)						
$\log(1+RE_t^{val})$			0.062^a	0.06^a	0.029^a			
			(0.002)	(0.002)	(0.0078)			
$\frac{RE_{t-1}^{val}}{K_{t-2}}$								0.089^a
								(0.002)
$\frac{RE_{t+1}^{val}}{K_t}$						-0.13^a		
						(0.0032)		
$\frac{RE_{t+2}^{val}}{K_{t+1}}$							-0.059^a	
							(0.002)	
$\frac{1}{K_{isc,t-1}}$		$.65^a$		$.65^a$		1.2^a	1.5^a	$.81^a$
		(0.0088)		(0.0088)		(0.017)	(0.026)	(0.016)
$\log(K_{isc,t-1})$					-0.066^a			
					(0.0047)			
CF_t	0.031^a	0.024^a	0.031^a	0.024^a		0.027^a	0.029^a	0.023^a
	(0.00026)	(0.00024)	(0.00026)	(0.00024)		(0.00032)	(0.00042)	(0.00028)
$\log(Cash_t)$					0.12^a			
					(0.0015)			
# Obs.	7,998,967	7,998,967	7,998,967	7,998,967	6,574,808	6,019,188	4,470,916	6,020,862
Adj. R^2	0.19	0.21	0.19	0.21	0.54	0.2	0.21	0.16

Notes: INV = tangible investment normalized by lagged stock of tangible assets $K_{isc,t-1}$. $log(1+Inv_t)$ = natural logarithm of 1+ tangible investment. RE Val_t = market value of real estate holdings in t, transformed through inverse hyperbolic sine or natural logarithm. $\frac{RE^{val}}{K}$ = market value of real estate holdings normalized by K, at various leads and lags. CF_t = firm's cash flow normalized by $K_{isc,t-1}$. $\log(Cash_t)$: natural logarithm of firm's cash flow. All estimations include initial controls (ROA, Age, Asset, Industry) × the price of real estate $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. ^{c}, ^{b}, ^{a} denote, respectively, significance at the 10%, 5%, and 1% levels.

Overall, Tables 5, 6, and 7 provide strong evidence of a positive relationship between real-estate value and tangible investment. Based on this, we believe can safely rely on equations (6) and (7) for the remainder of the analysis.

Estimations on subsamples. As exposed in Section 3.1, our dataset includes firm balance-sheets from two sources, *BRN* (combined to *FICUS* until 2007 and *DADS*) and *FARE* (combined with *DADS*). As reported in Table A.3, the firm coverage differs between the two administrative sources, with *BRN* covering a lower number of firms, on average larger. Conversely, the universe of firms covered by *FICUS-FARE* is larger, including much more firms, on average smaller. Therefore, we check in Table 8 how our key result behaves on each of this two datasets. In this regard, the second sample is restricted to firms whose data source is FARE (2009-2015) and which entered the dataset 2009 onwards. In that case, we ensure that the firm position in the initial distribution of performance is made within the FARE sample (that includes smaller- and here, also younger firms).

Qualitatively, the outcome is identical: The value of real-estate holdings has a positive impact on the investment ratio whatever the data source considered. The size of the effect differs however, consistently with the underlying characteristics of the firms in each database. Column (1) shows a smaller coefficient estimate (0.14) for the average *BRN* firm, which is bigger than the average *FICUS-FARE* firm. And for the latter, the coefficient is consistently twice bigger (0.3). Columns (2) and (4), reporting estimates based on the dummy variable for real-estate ownership interacted with real-estate prices, also show BRN firms owning some real estate increase their investment rate more than FICUS-FARE firms following an increase in real-estate prices, though the gap is smaller. Overall, these results are consistent with the idea of an heterogenous collateral channel along the size/performance distribution of firms. We investigate more systematically this intuition in the next section.

Table 8: Estimates on the different datasets

	(1)	(2)	(3)	(4)
Dep. Var	$INV_{isc,t}$			
Database	BRN (1994-2007)		FF (2009-2014)	
RE Value$_{isc,t}$	0.14^{a}		0.3^{a}	
	(0.0024)		(0.0069)	
$DumRE_0 \times P_t$		0.046^{a}		0.38^{a}
		(0.0031)		(0.042)
CF$_{isc,t}$	0.029^{a}	0.029^{a}	0.022^{a}	0.022^{a}
	(0.00041)	(0.00041)	(0.00034)	(0.00035)
$\frac{1}{K_{isc,t-1}}$	0.84^{a}	0.85^{a}	0.61^{a}	0.64^{a}
	(0.028)	(0.028)	(0.0099)	(0.011)
# Obs.	2,461,477	2,461,477	4,050,303	4,050,303
Adj. R^2	0.2	0.2	0.22	0.2

Notes: INV = tangible investment normalized by lagged stock of tangible assets K$_{isc,t-1}$. RE Value = market value of real estate holdings normalized by K$_{isc,t-1}$. $\widehat{P_t}$ = fitted value for the price of real estate, based on the first-stage regression. CF = firm's cash flow normalized by $K_{isc,t-1}$. All estimations include initial controls (ROA, Age, Asset, Industry) × the price of real estate $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. ^{c}, ^{b}, ^{a} denote, respectively, significance at the 10%, 5%, and 1% levels.

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4.2 Investigating heterogeneity

Section 2.2 suggests a heterogeneous impact of the collateral channel on investment is very likely. We bring this intuition to the data in Tables 9 and 10. More specifically, Table 9 reports estimates of our baseline specification weighted by the size of the balance-sheet (column (2)) and the number of employees (column (3)), as well as subsamples contrasting small (columns (4) and (5), restricting the sample to firms having at most 5 or 12 employees) and bigger firms (column (6), restricting the sample to firms having at least 50 employees). Compared to our baseline (column (1)), all estimates show results consistent with the idea that small (big) firms react more (less) to a collateral shock, as proxied by a rise the value of real-estate holdings: the estimated coefficient for big firms lies between 0.12 and 0.16 (columns (2), (3) and (6)), while it reaches 0.25-0.26 for small-sized firms (columns (4) and (5)). Therefore, it appears small firms react (roughly) twice more to a collateral shock than bigger ones.

Table 9: Collateral channel and size

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	$INV_{isc,t}$					
	baseline	Weight by:		Employment		
		Asset	Tot employment	$<= 5E$	$<= 12E$	$> 50E$
RE Value$_{isc,t}$	0.2^a	0.12^a	0.15^a	0.26^a	0.25^a	0.16^a
	(0.0039)	(0.0023)	(0.0062)	(0.006)	(0.0054)	(0.0049)
$\frac{1}{K_{t-1}}$	0.63^a	1.2^a	1.4^a	0.77^a	0.82^a	0.51^a
	(0.0085)	(0.02)	(0.079)	(0.015)	(0.014)	(0.01)
CF$_{isc,t}$	0.024^a	0.021^a	0.025^a	0.021^a	0.023^a	0.02^a
	(0.00024)	(0.00036)	(0.0012)	(0.00033)	(0.00029)	(0.00037)
# Obs.	7,998,967	7,967,121	5,956,409	2,912,472	4,529,483	1,907,369
Adj. R^2	0.21	0.18	0.22	0.21	0.2	0.22

Notes: INV = tangible investment normalized by lagged stock of tangible assets K$_{isc,t-1}$. RE Value = market value of real estate holdings normalized by K$_{isc,t-1}$. CF = firm's cash flow normalized by $K_{isc,t-1}$. All estimations include initial controls (ROA, Age, Asset, Industry) × the price of real estate $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. [c], [b], [a] denote, respectively, significance at the 10%, 5%, and 1% levels.

Table 10 deepens our investigation on firm-level heterogeneity by interacting our measure of real-estate holdings with bins (deciles) of three proxies of firm size/performance: real labor productivity (i.e., real value added per worker, column (1)), real value added (column (3)), and real turnover (column (5)). Commonly used in the literature, these three indicators make comparison and generalization possible based on CompNet data (see next section). Finally, columns (2), (4), and (6) show how our baseline results (i.e., based on Equation (3) behave on the respective samples where those performance indicators are available.

All estimates point to strong evidence of heterogeneous effects of a collateral shock on the firm's investment. The difference ranges from 1 to 2.5-3 between big and small firms. Overall effects are higher on the labor productivity sample (column(1)), where the average firm appears smaller, with an estimated coefficient of 0.3 for RE Value$_{isc,t}$ (column (2)). In any case, columns

(1), (3), and (5) support the larger or more performing the firm, the lower the financial constraints, the lower the sensitivity of investment to the collateral channel. In the next section, we explore aggregate and cross-country implications of those results.

Table 10: Collateral channel and firm performance

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var	$INV_{isc,t}$					
RE Value$_{isc,t}$ × Deciles of:	Real labor prod		Real VA		Real turnover	
$\leq P10$	0.52^a		0.26^a		0.31^a	
	(0.013)		(0.0092)		(0.011)	
$P10 - P20$	0.31^a		0.38^a		0.32^a	
	(0.011)		(0.013)		(0.01)	
$P20 - P30$	0.25^a		0.3^a		0.29^a	
	(0.01)		(0.0077)		(0.0078)	
$P30 - P40$	0.21^a		0.24^a		0.23^a	
	(0.01)		(0.0072)		(0.0068)	
$P40 - P50$	0.21^a		0.18^a		0.21^a	
	(0.0096)		(0.0053)		(0.0065)	
$P50 - P60$	0.17^a		0.14^a		0.18^a	
	(0.009)		(0.0043)		(0.005)	
$P60 - P70$	0.16^a		0.14^a		0.14^a	
	(0.0091)		(0.0044)		(0.0042)	
$P70 - P80$	0.18^a		0.12^a		0.13^a	
	(0.0094)		(0.0036)		(0.004)	
$P80 - P90$	0.16^a		0.11^a		0.11^a	
	(0.0094)		(0.0035)		(0.0036)	
$> P90$	0.19^a		0.073^a		0.077^a	
	(0.0097)		(0.0027)		(0.0024)	
RE Value$_{isc,t}$		0.3^a		0.2^a		0.2^a
		(0.0064)		(0.0039)		(0.0039)
CF$_{isc,t}$	0.025^a	0.025^a	0.024^a	0.024^a	0.024^a	0.024^a
	(0.00029)	(0.00029)	(0.00025)	(0.00025)	(0.00024)	(0.00024)
$\frac{1}{K_{t-1}}$	0.76^a	0.76^a	0.63^a	0.63^a	0.63^a	0.63^a
	(0.014)	(0.014)	(0.0086)	(0.0087)	(0.0084)	(0.0085)
# Obs.	4,121,206	4,121,206	7,579,499	7,579,499	7,998,938	7,998,938
Adj. R^2	0.19	0.19	0.21	0.21	0.21	0.21

Notes: INV = tangible investment normalized by lagged stock of tangible assets $K_{isc,t-1}$. RE Value = market value of real estate holdings normalized by $K_{isc,t-1}$. CF = firm's cash flow normalized by $K_{isc,t-1}$. All estimations include initial controls (ROA, Age, Asset, Industry) × the price of real estate $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. ^{c}, ^{b}, ^{a} denote, respectively, significance at the 10%, 5%, and 1% levels.

5 The Collateral Channel across European Countries

5.1 The choice of the country sample and the performance variable

The previous empirical exercise helps to recover micro/firm-level estimates of the reaction of investment to real estate value. The latter should correspond to the "true" elasticities for comparable countries, that, they should be the same for countries similar to France concerning both the weight of banks in corporate funding and real estate holding behavior. These two criteria drove us to select the following countries (time ranges in parentheses indicate the period surveyed in CompNet): Belgium (2004-2015), Denmark (2000-2015), Italy (2001-2014), Netherlands (2000-2014), Portugal (2006-2015), Spain (2006-2015), Sweden (2003-2015). For those countries, the reactions of investment to the real estate value estimated on French data should capture similar firm-level heterogeneity given sufficiently close levels of financial constraints.

Table A.4 shows the heterogeneous distribution of real labor productivity across the considered countries, which should translate into heterogeneous sensitivities of investment to real estate value shock.[15] The second major contribution of this paper is to provide a quantification of this heterogeneity, from which we recast the aggregate collateral channel in the various countries of our European sample as third contribution.

5.2 Assessing the comparability between French and Compnet data

Comparing distributions Before investigating the heterogenous size of the collateral channel on the sample of European countries, we check the consistency between the two databases of the performance distributions of French firms. Indeed, for our extension to other countries from the CompNet database to make sense, we need to be sure that estimates arising from the French and CompNet data to be as similar as possible. To this end, Table 11 compares estimates of the heterogenous impact of the collateral channel along labor productivity distribution based, as we do in Section 4.2, on threshold values (by deciles) obtained from French data (column (1)) or those from the Compnet dataset (i.e, the penultimate line of Table 3). In this regard, note we restrict the sample to firms with at least one employee, the latter being the focus of CompNet dataset. In any case, the estimated elasticities are very close between the two methods, for each decile of labor productivity.

Comparing aggregate collateral channel As second sanity check, we compute the aggregate sensitivity of investment to real estate value in France based on Equation (9) for our two sources of labor productivity thresholds. Specifically, we compute the weighted average of our estimates $\widehat{\rho}_j$ by bin j of real labor productivity using the thresholds from either the French

[15]This is also the case for the distribution of cash/asset, real value added and turnover (see Tables A.5, A.6 and A.7 in Appendix C even if we restrict our estimation for the collateral channel across Europe to the conditioning on labor productivity.

Table 11: Heterogenous collateral channel in France - French vs. CompNet data

	BFF deciles	Compnet deciles
	(1)	(2)
Dep. Var	$INV_{isc,t}$	
RE Value$_{isc,t}$ × Labor prod. decile:		
$\leq P10$	0.58^a	0.51^a
	(0.016)	(0.013)
$P10-P20$	0.34^a	0.26^a
	(0.012)	(0.0097)
$P20-P30$	0.26^a	0.21^a
	(0.01)	(0.0095)
$P30-P40$	0.22^a	0.2^a
	(0.01)	(0.0099)
$P40-P50$	0.22^a	0.2^a
	(0.0098)	(0.01)
$P50-P60$	0.2^a	0.18^a
	(0.0094)	(0.0095)
$P60-P70$	0.15^a	0.16^a
	(0.0085)	(0.0096)
$P70-P80$	0.2^a	0.17^a
	(0.011)	(0.01)
$P80-P90$	0.16^a	0.18^a
	(0.009)	(0.011)
$> P90$	0.21^a	0.22^a
	(0.011)	(0.013)
CF$_{isc,t}$	0.025^a	0.025^a
	(0.0003)	(0.0003)
$\frac{1}{K_{t-1}}$	0.88^a	0.88^a
	(0.016)	(0.016)
# Obs.	4,021,988	4,021,988
Adj. R^2	0.19	0.19

Notes: INV = tangible investment normalized by lagged stock of tangible assets K$_{isc,t-1}$. BFF = French firm-level data (BRN FICUS FARE). RE Value = market value of real estate holdings normalized by K$_{isc,t-1}$. CF = firm's cash flow normalized by $K_{isc,t-1}$. All estimations include initial controls (ROA, Age, Asset, Industry) × the price of real estate $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. ^{c}, ^{b}, ^{a} denote, respectively, significance at the 10%, 5%, and 1% levels.

or Compnet data for France (see Table 11), combined with the weighting scheme based on the share of capital by labor productivity decile (see Table 4). The aggregate elasticities are reported in Table 12, and show up as extremely similar. We can hence move on to use the CompNet labor productivity thresholds obtained on other EU countries to infer the (heterogeneous and aggregate) size of the collateral channel there.

Table 12: From micro to macro: The French case

Using "BFF" elasticities	0.21
Using "Compnet" elasticities	0.2

5.3 Estimates of collateral channel cross countries

Distribution of elasticities by labor productivity deciles Table 13 shows distribution of the investment sensitivity to real estate shocks across the selected EU countries, conditional on heterogeneity in real labor productivity. Figure 1 graphically represents those results.

Figure 1: Estimates of the heterogenous collateral channel - selected EU countries

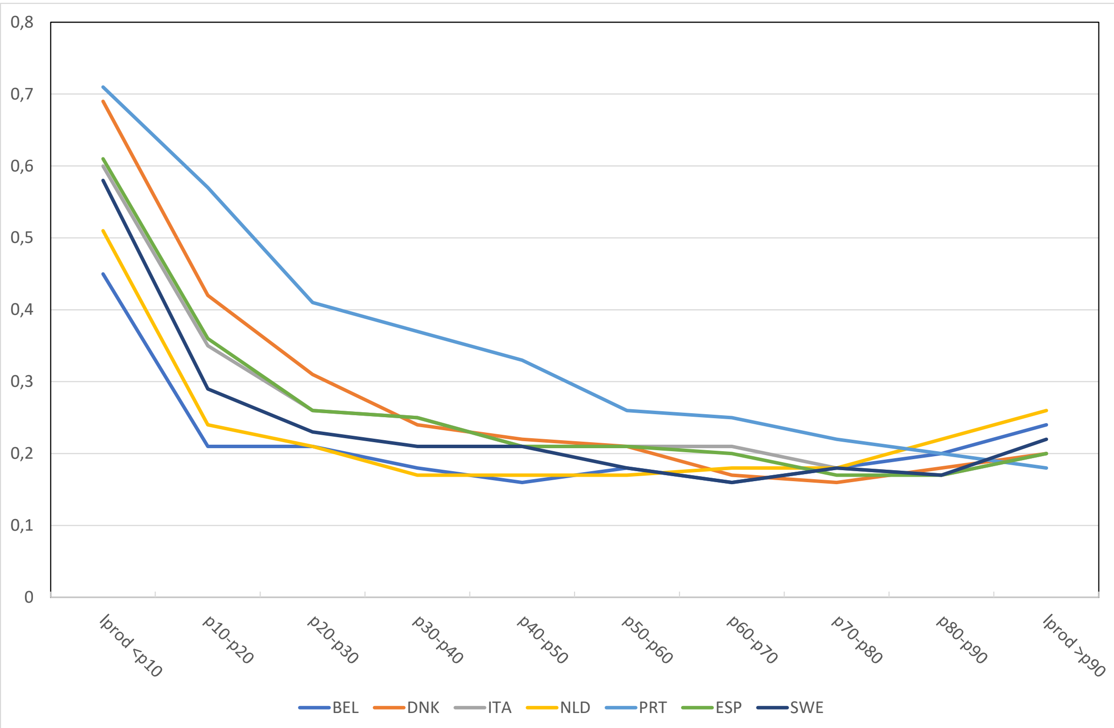


Table 13: Estimates of the heterogenous collateral channel - selected EU countries

Country:	BEL	DNK	ITA	NLD	PRT	ESP	SWE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var				$INV_{isc,t}$			
RE Value$_{isc,t}$ × country's labor prod. decile							
$\leq P10$	0.45^a	0.69^a	0.6^a	0.51^a	0.71^a	0.61^a	0.58^a
	(0.011)	(0.019)	(0.016)	(0.013)	(0.022)	(0.016)	(0.015)
$P10-P20$	0.21^a	0.42^a	0.35^a	0.24^a	0.57^a	0.36^a	0.29^a
	(0.0081)	(0.016)	(0.013)	(0.0078)	(0.021)	(0.013)	(0.0094)
$P20-P30$	0.21^a	0.31^a	0.26^a	0.21^a	0.41^a	0.26^a	0.23^a
	(0.009)	(0.01)	(0.011)	(0.0081)	(0.02)	(0.011)	(0.0094)
$P30-P40$	0.18^a	0.24^a	0.25^a	0.17^a	0.37^a	0.25^a	0.21^a
	(0.0095)	(0.009)	(0.012)	(0.0083)	(0.019)	(0.012)	(0.0098)
$P40-P50$	0.16^a	0.22^a	0.21^a	0.17^a	0.33^a	0.21^a	0.21^a
	(0.01)	(0.0095)	(0.011)	(0.0094)	(0.016)	(0.011)	(0.01)
$P50-P60$	0.18^a	0.21^a	0.21^a	0.17^a	0.26^a	0.21^a	0.18^a
	(0.011)	(0.0099)	(0.011)	(0.01)	(0.013)	(0.011)	(0.0096)
$P60-P70$	0.16^a	0.17^a	0.21^a	0.18^a	0.25^a	0.2^a	0.16^a
	(0.011)	(0.0093)	(0.0099)	(0.013)	(0.012)	(0.0096)	(0.0097)
$P70-P80$	0.18^a	0.16^a	0.18^a	0.18^a	0.22^a	0.17^a	0.18^a
	(0.013)	(0.0094)	(0.0086)	(0.013)	(0.0088)	(0.0086)	(0.0092)
$P80-P90$	0.2^a	0.18^a	0.17^a	0.22^a	0.2^a	0.17^a	0.17^a
	(0.015)	(0.0087)	(0.0073)	(0.017)	(0.0067)	(0.0073)	(0.01)
$> P90$	0.24^a	0.2^a	0.2^a	0.26^a	0.18^a	0.2^a	0.22^a
	(0.017)	(0.0084)	(0.0078)	(0.024)	(0.0056)	(0.0081)	(0.011)
CF$_{isc,t}$	0.025^a	0.025^a	0.025^a	0.025^a	0.025^a	0.025^a	0.025^a
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\frac{1}{K_{t-1}}$	0.88^a	0.88^a	0.88^a	0.88^a	0.88^a	0.88^a	0.88^a
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
# Obs.	4,021,988	4,021,988	4,021,988	4,021,988	4,021,988	4,021,988	4,021,988
Adj. R^2	0.19	0.19	0.19	0.19	0.19	0.19	0.19

Notes: INV = tangible investment normalized by lagged stock of tangible assets $K_{isc,t-1}$. BFF = French firm-level data (BRN FICUS FARE). RE Value = market value of real estate holdings normalized by $K_{isc,t-1}$. CF = firm's cash flow normalized by $K_{isc,t-1}$. All estimations include initial controls (ROA, Age, Asset, Industry) × the price of real estate $P_{c,t}$, as well as firm- and strate-year-fixed effects. Standard errors in parentheses, clustered at the strate-year level. ^{c}, ^{b}, ^{a} denote, respectively, significance at the 10%, 5%, and 1% levels. The sample of French firms is restricted to those with minimum one employee.

The decreasing importance of the collateral channel along the productivity distribution is a shared characteristic of the selected countries, and is particularly strong until the median of the distribution. There are also some interesting between-countries differences, reflecting some countries having a higher proportion of small/less productive firms. This is particularly striking for Portugal, with estimated impacts of the collateral channel reaching 0.7 for the first decile, and still above 0.3 at the median. To a lesser extent, Denmark, Italy, and Spain also display a more intense collateral channel, but mostly concentrated in the two or three first deciles. In the upper deciles (above the median), quantifications are overall close across European countries, though not exactly identical. In the two last deciles, the estimated sensitivity to real-estate ranges between 0.17 and 0.26. We next derive the aggregate implications of those results.

From micro to macro: In EU countries The first row of Table 14 reports the aggregate semi-elasticity of investment to the collateral value for each considered EU country. To this end, following Equation (9), for each country we compute a weighted mean of estimated investment sensitivity for each labor productivity decile (Table 13), with weights being the shares of capital corresponding to each decile (Table 4). By contrast, the second row of Table 14 reports for each country the simple, arithmetic mean of the same, (labor-productivity) decile-specific investment sensitivity.

Table 14: From micro to macro: EU countries

Country	BEL	DNK	ITA	NLD	PRT	ESP	SWE
Aggregate elasticity	0.214	0.201	0.214	0.216	0.248	0.218	0.212
Mean elasticity	0.217	0.280	0.264	0.231	0.350	0.264	0.243

Notes: Authors' calculations, using results reported in Tables 13 and 4.

Contrasting results reported in Tables 13 and 14 is enlightening. As previously noted, the selected European countries display marked heterogeneity in the collateral channel estimates in the bottom deciles of the distribution, which translate in significant heterogeneity of the *mean* elasticity, ranging between 0.217 and 0.35. However, heterogeneity is much more limited in the upper deciles, which on the other hand represent often more than half, and sometimes up to three quarters of the aggregate capital stock (see Table 4, and also Tables A.8 and A.9 for more details). Consistently with the literature pointing to the crucial role played by large firms in shaping aggregate dynamics (see e.g., Carvalho and Grassi, 2019, Gabaix, 2011, di Giovanni et al., 2014), this translates into a limited variance for the aggregate elasticity, ranging between 0.2 and 0.25, and evolving around 0.21 in most cases. Therefore, the cross-country heterogeneity of the aggregate collateral channel within the EU seems limited, at least for the selected countries.

6 Conclusion

Based on firm-level evidence for France and several EU countries over various time spans between 1994 and 2015, this paper emphasizes two main results regarding within- and between-countries heterogeneity of the collateral channel, measured by the value of real-estate holdings. Based on an exhaustive French firm-level database, we first show the heterogenous importance of the collateral channel for investment, along the distributions of various performance and size indicators. While the sensitivity of investment to real estate value for the average firm is equal to 0.2, the difference ranges from 1 to 3 between big (0.07-0.2) and small (0.3-0.5) firms. In other words, the effect of a collateral shock on investment is much stronger for small firms, below the median of the distribution of labor productivity, turnover and value added. Extending these results to comparable EU countries (Belgium, Denmark, Italy, Netherlands, Portugal, Spain, and Sweden), we point to similar, substantial differences in investment reactions across the considered countries, due to the underlying heterogeneity in the distributions of firms' performance.

We then use these micro-founded estimates of investment dependence on firms real-estate holdings conditional on size to derive country-level, aggregate measures of the collateral channel. There is some non-negligible between-countries heterogeneity regarding small firms (below the median), translating into mean elasticities ranging between 0.22 and 0.35. However, heterogeneity is much more limited in the upper deciles, which shape most of the aggregate dynamics. This brings an aggregate sensitivity of investment to the collateral value between 0.2 and .025, supporting limited heterogeneity of the collateral channel across the EU countries considered.

Our work has interesting policy implications regarding the functioning of the Economic and Monetary Union. While the aggregate effects of collateral shocks may not substantially differ across EU countries, they have marked heterogenous effects across firms within each EU country. Accordingly, the economic effects of financial shocks should rather be a concern for national authorities than at the centralized (i.e, European Central Bank) level.

References

Allen, F., Gale, D., 2001. Comparing Financial Systems. volume 1 of *MIT Press Books*. The MIT Press. URL: https://ideas.repec.org/b/mtp/titles/0262511258.html.

Asdrubali, P., Hallak, I., Harastoszi, P., 2022. Financial Constraints of EU firms: A Sectoral Analysis. JRC Research Reports JRC130317. Joint Research Centre (Seville site). URL: https://ideas.repec.org/p/ipt/iptwpa/jrc130317.html.

Badarau, C., Levieuge, G., 2013. Financial Heterogeneity in a Monetary Union. Journal of Economic Integration 28, 482–506.

Badarau-Semenescu, C., Levieuge, G., 2010. Assessing the Potential Strength of a Bank Capital Channel in Europe: A Principal Component Analysis. The Review of Finance and Banking 2, 005–016. URL: https://ideas.repec.org/a/rfb/journl/v02y2010i1p005-016.html.

Bahaj, S., Foulis, A., Pinter, G., 2020. Home values and firm behavior. The American Economic Review 110, pp. 2225–2270. URL: https://www.jstor.org/stable/26921635.

Banerjee, R., Blickle, K., 2021. Financial frictions, real estate collateral and small firm activity in europe. European Economic Review forthcoming.

Barro, R.J., 1976. The Loan Market, Collateral, and Rates of Interest. Journal of Money, Credit and Banking 8, 439–456.

Bartlett, R., Partnoy, F., 2020. The Ratio Problem. SSRN Working Papers. URL: http://dx.doi.org/10.2139/ssrn.3605606.

Beck, T., Demirgüç-kunt, A., Maksimovic, V., 2005. Financial and legal constraints to growth: Does firm size matter? Journal of Finance 60, 137–177. URL: https://EconPapers.repec.org/RePEc:bla:jfinan:v:60:y:2005:i:1:p:137-177.

Bernanke, B., Gertler, M., 1989. Agency Costs, Net Worth, and Business Fluctuations. American Economic Review 79, 14–31. URL: https://ideas.repec.org/a/aea/aecrev/v79y1989i1p14-31.html.

Bond, S., Meghir, C., 1994. Dynamic investment models and the firm's financial policy. Review of Economic Studies 61, 197–222. URL: https://EconPapers.repec.org/RePEc:oup:restud:v:61:y:1994:i:2:p:197-222.

Carvalho, V., Grassi, B., 2019. Large firm dynamics and the business cycle. American Economic Review 109, 1375–1425.

Catherine, S., Chaney, T., Huang, Z., Sraer, D., Thesmar, D., 2022. Quantifying reduced-form evidence on collateral constraints. Journal of Finance 77, 2143–2181.

Chaney, T., Sraer, D., Thesmar, D., 2009. The Collateral Channel: How Real Estate Shocks Affect Corporate Investment. Technical Report.

Chaney, T., Sraer, D., Thesmar, D., 2012. The collateral channel: How real estate shocks affect corporate investment. American Economic Review 102, 2381–2409.

Chaney, T., Sraer, D., Thesmar, D., 2020. Response to Welch (2020) Real Estate Collateral Does Affect Investment. SSRN Working Papers. URL: http://dx.doi.org/10.2139/ssrn.3599277.

Chapelle, G., Eyméoud, J.B., 2018. The cost of agglomeration and the housing supply elasticity : The extensive and intensive margin housing supply elasticities. Technical Report.

Compnet, 2018. CompNet's 6th vintage of data: Novelties and main stylised facts. Cross-country report. The Competitiveness Research Network. URL: https://www.comp-net.org/fileadmin/_compnet/user_upload/Documents/Cross-country_report_updated_28.02.2018.pdf.

Driver, C., Muñoz-Bugarin, J., 2019. Financial constraints on investment: Effects of firm size and the financial crisis. Research in International Business and Finance 47, 441–457. URL: https://EconPapers.repec.org/RePEc:eee:riibaf:v:47:y:2019:i:c:p:441-457.

Ehrmann, M., Gambacorta, L., Martínez Pagés, J., Sevestre, P., Worms, A., 2001. Financial systems and the role of banks in monetary policy transmission in the euro area. Working Paper Series 105. European Central Bank.

European Central Bank, 2012. Heterogeneity in Euro Area: Financial Conditions and Policy Implications. ECB Monthly Bulletin. European Central Bank. URL: https://www.ecb.europa.eu/pub/pdf/other/art1_mb201208en_pp63-75en.pdf.

Fougere, D., Lecat, R., Ray, S., 2019. Real estate prices and corporate investment: Theory and evidence of heterogeneous effects across firms. Journal of Money, Credit and Banking 51, 1503–1546.

Gabaix, X., 2011. The granular origins of aggregate fluctuations. Econometrica 79, 733–772.

Gilchrist, S., Himmelberg, C., 1998. Investment, Fundamentals and Finance. NBER Working Papers 6652. National Bureau of Economic Research, Inc. URL: https://EconPapers.repec.org/RePEc:nbr:nberwo:6652.

di Giovanni, J., Levchenko, A.A., Mejean, I., 2014. Firms, destinations, and aggregate fluctuations. Econometrica 82, 1303–1340. URL: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA11041, doi:https://doi.org/10.3982/ECTA11041, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA11041.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L., Villegas-Sanchez, C., 2017. Capital allocation and productivity in south europe. The Quarterly Journal of Economics 132, 1915–1967.

Grjebine, T., Héricourt, J., Tripier, F., 2023. Sectoral reallocations, real estate shocks, and productivity divergence in europe. Review of World Economics (Weltwirtschaftliches Archiv) 159, 101–132. URL: https://EconPapers.repec.org/RePEc:spr:weltar:v:159:y:2023:i:1:d:10.1007_s10290-022-00464-3.

Hart, O., Moore, J., 1994. A theory of debt based on the inalienability of human capital. The Quarterly Journal of Economics 109, 841–879.

Kiyotaki, N., Moore, J., 1997. Credit Cycles. Journal of Political Economy 105, 211–248. URL: https://ideas.repec.org/a/ucp/jpolec/v105y1997i2p211-48.html.

Love, I., 2003. Financial development and financing constraints: International evidence from the structural investment model. Review of Financial Studies 16, 765–791. URL: https://EconPapers.repec.org/RePEc:oup:rfinst:v:16:y:2003:i:3:p:765-791.

Moulton, B.R., 1990. An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Unit. The Review of Economics and Statistics 72, 334–338. URL: https://ideas.repec.org/a/tpr/restat/v72y1990i2p334-38.html.

Saiz, A., 2010. The geographic determinants of housing supply. The Quarterly Journal of Economics 125, 1253–1296.

Stiglitz, J., Weiss, A., 1981. Credit rationing in markets with imperfect information. American Economic Review 71, 393–410.

Welch, I., 2021. Spurious Inference Caused by Time-Series Variation in Scaling: Real Estate Shocks Did Not Affect Corporate Investment. SSRN Working Papers. URL: http://dx.doi.org/10.2139/ssrn.3599280.

A Data Appendix

A.1 French database

A.1.1 Firm-level data: Sources and treatment

Our firm-level database combines three firm-level balance-sheets (obtained from the INSEE): *Fichier complet unifié de Suse* (FICUS, 1994-2007), *Bénéfices Réels Normaux* (BRN, 1993-2009), *Fichier approché des résultats d'Esane* (FARE, 2009-2015), *Déclaration Annuelle de Données Sociales* (DADS, 1993-2015). We combine these various datasets to maximize coverage and data availability.

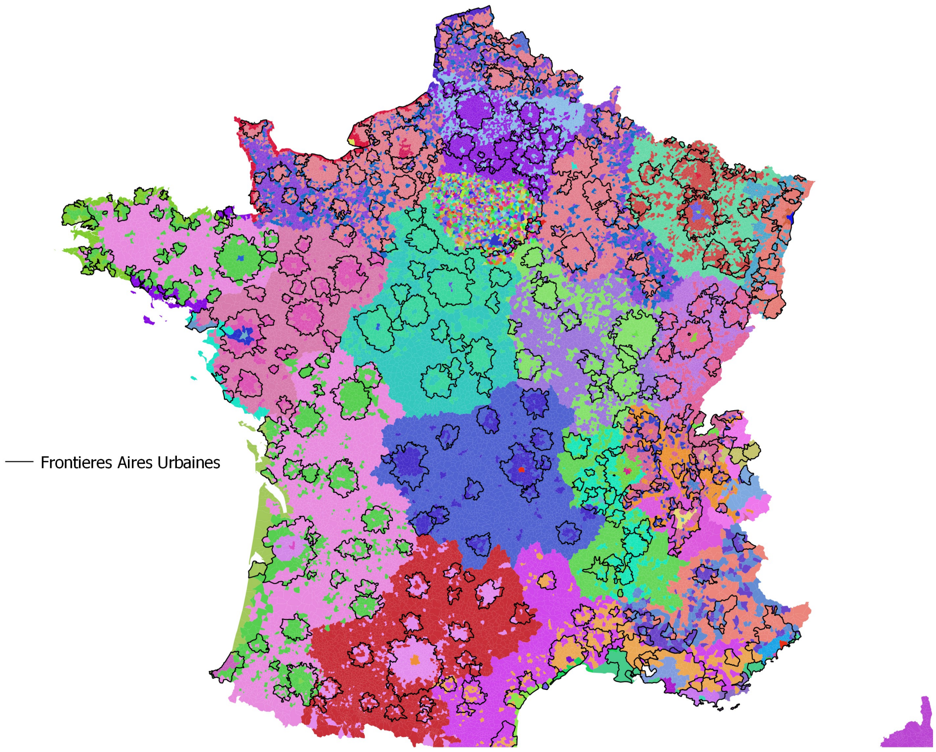
Investment (dependent variable) is reported in FICUS and FARE, but not in BRN - unavailable in 2008. Location (city) of firms is reported only in DADS. Some variables are simultaneously reported in FICUS and BRN (1994-2007) and in FARE and BRN (2009). In this case, we use BRN values for most variables except if missing in BRN, and except for value-added and firm's age, for which we use FARE information in 2009 by default (as more firms are covered). For employment data (number of employees), we use DADS values if missing in BRN/FICUS/FARE.

A.1.2 The IV sample

Building the instrumental variable We adopt the same methodology as in Chaney et al. (2012) or Fougere et al. (2019) to construct the instrument for local housing prices. We combine the housing loan interest rate series provided by the *Banque de France* with the housing supply elasticity computed by Chapelle and Eyméoud (2018). Specifically we use their extensive housing supply elasticity series for France (at the "urban area" level) estimated with the Saiz' (2010) specification. Considering the *extensive* elasticity takes into account the fact that the city size may vary with housing prices (in contrast to the intensive (short-run) elasticity); accordingly, when they estimate the inverse housing supply, their dependent variable is the growth rate of housing prices between 1999 and 2012; their key explicative variable being the change in housing units over the same period, which they instrument following Saiz (2010) using local temperature in January and population in 1911 (see Chapelle and Eyméoud (2018) for more details).

Strates and urban areas The housing supply elasticity is measured at the "urban area" level ("*aire urbaine*"), which does not correspond with the Notaries' "strates". In particular, locations in weakly dense areas are excluded from the urban area coverage. This is made explicit in Figure A.2. Each "strate" is represented by a given color (depending on the density of the strate, it can be either a district, as in Paris, a city or a department in less populated areas). Each urban area is identified through its frontier identified by a thin black line.

Figure A.2: France: strates and urban areas



As can be inferred from Figure A.2, the IV sample represents a much reduced geographical coverage relative to the full sample. Provided we check that the baseline sample is immune from any endogeneity issue, this drives us to favor investigating the heterogeneity in the collateral channel on the full sample.

A.1.3 From the real estate at historical cost to market value

Following the standard definition, three major categories of property, plant and equipment are considered as real estate assets: buildings, land and equipments. In the firms' balance sheets, they are reported valued at historical cost rather than marked-to-market. Following Chaney et al. (2012) or Fougere et al. (2019), we adopt a two-step procedure to switch the historical cost to the market value. First, we estimate the age of the properties, or equivalently the year of acquisition. Second, with this in hand, we build the market value of real estate assets making us of the housing prices series obtained at the local level from the French notaries.

In this Appendix, we describe the method for obtaining the age of properties in more details. All the procedure is run at the firm-year level. The age of the property is the product of its depreciable life times the proportion of the property claimed as depreciation. We uncover both pieces of information from the firm' accounting data. This requires the calculation of the real estate assets depreciation. Since land does not depreciate, this drives us to exclude firms which declare real estate assets as only land.

First, consider the depreciable life. As defined in Chaney et al. (2012), it is equal to building cost over annual depreciation. We proxy the building cost by the tangible assets on buildings (*immobilisations corporelles sur les constructions*). As for the denominator, we only dispose of the depreciation and amortization expenses for total fixed assets (*amortissement sur immobilisations totales*). We hence multiply this variable by the ratio of tangible assets on buildings over total fixed assets (*immobilisations corporelles sur les constructions/immobilisations totales*) to get closer to depreciation for buildings. This gives us the depreciable life of the assets, by firm-year. We obtain an average value of 36 years, which we will use to calculate the average year of the real estate properties. Notice that this is consistent with the value of 40 years retained by Chaney et al. (2012).

Second, we need to calculate the proportion of buildings claimed as depreciation. This is equal to the accumulated depreciation on buildings over their gross book value. This is straightforward in BRN data, which contains the adequate item for accumulated depreciation on buildings (*amortissement sur constructions*). In FARE data, we only have information on accumulated depreciations and allowances for depreciation on tangible assets (*amortissements et provisions sur immobilisations corporelles*). We proxy the accumulated depreciation on buildings by multiplying the depreciation on tangible assets by the ratio of (tangible assets on buildings/total tangible assets). We then divide accumulated depreciation on buildings by their gross book value (*immobilisations corporelles sur les constructions*). On average, the proportion of buildings claimed as depreciation is 0.38. Notice that the richness of information in our accounting dataset allows us to retrieve this information for all years over 1994-2014. Accordingly, we can keep the firms whenever they enter the dataset, even if not the first year of our sample.[16]

As last step, we calculate the age of the properties as the proportion claimed for depreciation times the average depreciable life. All these steps are run for the properties declared by the firm the first year of entry in the database (say, year 0). Taking the difference between this year 0 and the age of the building gives us the year of acquisition. For each year in the database, we then infer the market value of real estate holdings by inflating their historical cost with "strate"-level residential real estate inflation from the year of acquisition and the current year of observation.

[16]This contrasts with CST (2012). They are compelled to keep firms only already present in 1993, i.e. the first year of their database, as the item used to calculate the claimed depreciation of buildings is no longer in Compustat after 1993.

A.2 More on French firm data

A.2.1 From the real estate at historical cost to market value

Following the standard definition, three major categories of property, plant and equipment are considered as real estate assets: buildings, land and equipments. In the firms' balance sheets, they are reported valued at historical cost rather than marked-to-market. Following Chaney et al. (2012) or Fougere et al. (2019), we adopt a two-step procedure to switch the historical cost to the market value. First, we estimate the age of the properties, or equivalently the year of acquisition. Second, with this in hand, we build the market value of real estate assets making us of the housing prices series obtained at the local level from the French notaries.

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A.3 More descriptive Statistics

Some statistics linked to the real estate status Table A.1 provides some statistics on the proportion of firms with and without real estate properties (still including those with only land at this stage). Given the negligible share of firms with real estate as only land, we are confident that removing them from the subsequent analysis will not alter our estimation results.

Table A.1: French firms data, depending on real estate status

	Large sample			IV sample		
	All firms	With RE	No RE	All firms	With RE	No RE
Nb of firms	710318	185190	525128	230706	182478	48228
%	-	0.31	0.69	-	0.24	0.61
Share with pos. inv.	0.64	0.73	0.60	0.61	0.71	0.59
Avg raw investment	25.81	43.88	19.14	21.62	40.16	17.12

Among firms with RE			
Share with	only land	only buildings	with land and building
Full sample	0.032	0.619	0.350
IV sample	0.020	0.709	0.271

Mean value over the period, based on statistics calculated on a yearly basis. Investment is expressed in thousands of euros.

Table A.2 provides similar descriptive statistics as in Table 1 (after removing the firms with real estate as land only), distinguishing firms depending on their real estate status.

Descriptive statistics depending on the source of administrative data Table A.3 reports descriptive statistics distinguishing firms depending on the data source, BRN or FARE. As expected, firms only in the BRN sample (over 1994-2007) are older and larger in size of assets and total sales. If their value added and number of employees are also larger, their labor productivity is yet below the one obtained on the more exhaustive FARE sample. These differences justify that we check the consistency of our elasticity estimates on each sub-sample separately.

[17] This contrasts with CST (2012). They are compelled to keep firms only already present in 1993, i.e. the first year of their database, as the item used to calculate the claimed depreciation of buildings is no longer in Compustat after 1993.

Table A.2: France: Full sample, depending on the real estate status

	Mean			Median			Standard deviation		
RE status:	All	Pos RE	No RE	All	Pos RE	No RE	All	Pos RE	No RE
PH_{isct}	0.26	0.67	0	0.00	0.54	0	0.54	0.69	0
Age	12.84	13.84	12.51	9.00	10.00	8.00	13.94	13.52	14.07
Asset	507.38	928.11	362.50	95.81	196.70	78.25	1450.89	2128.37	1090.01
Total sales	731.33	1263.78	547.97	137.51	172.44	132.65	2665.46	3761.67	2132.10
CF_{isct}	0.86	0.38	1.07	0.27	0.17	0.38	2.54	1.21	2.92
Nb of employees	14.99	20.95	12.90	5.00	8.00	4.00	82.88	69.66	86.95
I_{isct}	0.16	0.11	0.19	0.03	0.04	0.02	0.41	0.30	0.45
Labor pdvty	41.86	36.43	43.79	29.94	29.50	30.13	102.56	47.61	115.98
Lev. ratio (fin. debt)	0.19	0.20	0.18	0.14	0.20	0.09	0.20	0.16	0.22
Lev. ratio (total debt)	0.56	0.52	0.57	0.55	0.55	0.55	0.29	0.22	0.32
ROA	0.06	0.04	0.07	0.04	0.03	0.05	0.19	0.11	0.22
Nb firms-year	2916278	1177877	2069120	2916278	1177877	2069120	0	0	0
Nb firms per year	705956.25	180828.50	525127.69	236729	78717.5	152917.5	725104.75	192073.63	565778.75
Nb years per firm	5.33	3.38	5.58	5	2	5	3.84	3.67	3.35

Note: authors' computations. ROA: Return on Assets. The number of years refers to the number of years in the database. Firms whose real estate is only land are excluded.

Table A.3: French firms data, by origin dataset

	Mean			median			p25			p75		
	BFF 1994-2015	BRN 1994-2007	FF 2009-2015	BFF 1994-2015	BRN 1994-2007	FF 2009-2015	BFF 1994-2015	BRN 1994-2007	FF 2009-2015	BFF 1994-2015	BRN 1994-2007	FF 2009-2015
PH_{isct}	0.22	0.16	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.49
Age	12.31	12.86	11.64	8.00	9.00	7.00	4.00	4.00	3.00	17.00	17.00	17.00
Asset	503.46	1111.73	155.86	87.86	434.00	33.54	7.56	197.00	0.00	363.51	1019.12	110.03
Total sales	741.86	1774.08	195.97	137.21	629.00	72.58	45.95	282.18	25.85	471.22	1484.85	164.40
CF_{isct}	1.00	0.80	1.19	0.31	0.29	0.35	0.08	0.07	0.09	0.98	0.85	1.13
Total employment	16.54	23.58	6.71	5.00	8.00	2.00	2.00	4.00	1.00	12.00	18.00	5.00
I_{isct}	0.18	0.19	0.18	0.03	0.05	0.00	0.00	0.00	0.00	0.13	0.18	0.10
Labor productivity	43.38	37.24	46.01	30.56	29.14	28.35	16.68	17.26	14.20	52.15	45.30	56.22
Real labor prodvty.	0.45	0.42	0.46	0.32	0.32	0.28	0.18	0.19	0.14	0.55	0.50	0.56
ROA	0.06	0.05	0.07	0.04	0.04	0.03	0.00	0.00	0.00	0.11	0.10	0.13
Real turnover	7.97	20.64	1.92	1.37	7.33	0.71	0.45	3.29	0.25	4.96	17.19	1.61
Real value-added	2.59	5.90	0.88	0.70	2.59	0.39	0.21	1.21	0.09	2.08	5.64	0.91
Value-added	245.01	530.50	86.65	67.42	232.18	37.72	19.29	107.00	7.13	197.00	509.00	89.32
Nb firms-years	1005373	172703	820802	1005373	172703	820802	1005373	172703	820802	1005373	172703	820802
Nb firms/year	451154	76214	489050	539395	74347	473610	496445	72076	438145	572102	79044	553845
Nb years/firm	11.89	8.98	5.30	7.00	9.00	6.00	4.00	5.00	4.00	8.00	13.00	7.00

BFF, for BRN-FICUS-FARE, covering the whole sample of firms over 1994-2015. BRN: the sample of firms from BRN sources, over 1994-2007. FF: sample of firms from FICUS-FARE sources, over the period 2009-2015.

B More on the methodological strategy

B.1 Heterogeneity and aggregation

Define the financial accelerator as the response of (aggregate) investment to changes in the aggregate price of collateral, whose proxy here is the average price of real estate assets. Partitioning firms into bins j (deciles) of a given performance variable, then the aggregate financial accelerator ρ can be decomposed into:

$$\begin{aligned}\rho = \frac{\partial I}{\partial REVal} &= \sum_j \frac{\partial I_j}{\partial REVal_j}\frac{\partial REVal_j}{\partial REVal} \\ &= \sum_j \omega_j \rho_j, \end{aligned} \tag{11}$$

where ω_j represents the weight of the j^{th} bin in total real estate asset holdings.

The demonstration of this result is as follows. To keep that simple, consider only two categories, below / above the median, and the performance is the labor productivity. From the quantile regression, we have $\frac{\partial I}{\partial REVal}|_{lprod \leq P50}$, say $\frac{\partial I_1}{\partial REVal}$; and $\frac{\partial I}{\partial REVal}|_{lprod > P50}$, say $\frac{\partial I_2}{\partial RE}$.

By definition, $I = \sum_j I_i|_{lprod_i \leq P50} + \sum_j I_i|_{lprod_i > P50} = I_1 + I_2$, as well as $REVal = \sum_i REVal_i|_{lprod_i \leq P50} + \sum_j REVal_i|_{lprod_i > P50} = RE_1 + RE_2$. Accordingly, we can write:

$$\begin{aligned}\frac{\partial I}{\partial REVal} &= \frac{\partial\left[\sum_i I_i|_{lprod_i \leq P50} + \sum_i I_i|_{lprod_i > P50}\right]}{\partial\left[\sum_i REVal_i|_{lprod_i \leq P50} + \sum_i REVal_i|_{lprod_i > P50}\right]} \\ &= \frac{\partial(I_1 + I_2)}{\partial(REVal_1 + REVal_2)}\end{aligned}$$

Under the assumption of independence between investment across firms, we can simplify:

$$\frac{\partial I}{\partial REVal} = \frac{\partial I_1}{\partial(REVal_1 + REVal_2)} + \frac{\partial I_2}{\partial(REVal_1 + REVal_2)} \tag{12}$$

$$= \frac{\partial I_1}{\partial REVal_1}\frac{\partial REVal_1}{\partial(REVal_1 + REVal_2)} + \frac{\partial I_2}{\partial REVal_2}\frac{\partial REVal_2}{\partial(REVal_1 + REVal_2)} \tag{13}$$

We have estimated $\frac{\partial I_1}{\partial REVal_1} = \widehat{\rho}_1$ and $\frac{\partial I_2}{\partial REVal_2} = \widehat{\rho}_2$ from the "quantile" regression.

As next step, we need to get $\frac{\partial REVal_1}{\partial(REVal_1 + REVal_2)}$. At this point, it is helpful to remember the definition of $REVal$ as the real estate *value*. For a firm i (dropping the time, geographical and sector indices t, c, s for reading clarity), we have defined $REVal_i = P \times RE^{vol}_{i,0}$, with $RE^{vol}_{i,0}$ firm

i's initial real estate holdings (in normalized terms). Accordingly, we can rewrite:[18]

$$\begin{aligned} REVal_{lprod_i<p50} &= \sum_{lprod_i<p50} RE_i^{vol} P \\ &= P \times \sum_{lprod_i<p50} RE_i^{vol}, \end{aligned} \tag{14}$$

From this, we obtain that for each bin $j = 1, 2$ of the labor productivity distribution, $REVal_j = P \times RE_j^{vol}$ with RE_j^{vol} the normalized real estate holding of all firms in the j^{th} of the labor productivity distribution. Extending this to the whole distribution, we have that $RE_T = P \times RE_T^{vol}$ with RE_T^{vol} the normalized aggregate real estate holdings.[19] Importantly, both RE_j^{vol} ($j = 1, 2$) and RE_T^{vol} are independent from the housing price P. Accordingly (and it is the whole point of Chaney et al. (2012)), a shock on the collateral value at time t is a shock on the housing price conditional on a given real estate volume, such that:

$$\partial REVal_1 = RE_1^{vol} \partial P, \quad \partial REVal_T = RE_T^{vol} \partial P$$

Coming back to Equation (13), we have

$$\begin{aligned} \frac{\partial I}{\partial REVal} &= \widehat{\rho}_1 \frac{\partial RE_1}{\partial RE_T} + \widehat{\rho}_2 \frac{\partial RE_2}{\partial RE_T} \\ &= \widehat{\rho}_1 \frac{RE_1^{vol} \times \partial P}{RE_T^{vol} \times \partial P} + \widehat{\rho}_2 \frac{RE_2^{vol} \times \partial P_t}{RE_T^{vol} \times \partial P} \end{aligned}$$

Eliminating the term in ∂P, we finally get:

$$\frac{\partial I}{\partial REVal} = \widehat{\rho}_1 \frac{RE_1^{vol}}{RE_T^{vol}} + \widehat{\rho}_2 \frac{RE_2^{vol}}{RE_T^{vol}}$$

Denoting ω_j the ratio $\frac{RE_j^{vol}}{RE_T^{vol}}$ associated with firms in the j^{th} of the labor productivity distribution, we can rebuild the aggregate elasticity from disaggregated ones through:

[18] Specifically, for a firm i in location c at time t, the real estate value is defined as: $REVal_{ict} = P_{ct} RE_{i,t-1}^{vol,0}$ with $RE_{i,t-1}^{vol,0} \equiv \frac{H_i^0}{PPE_{i,t-1}}$. H_i^0 is the volume of real estate holdings the first year of acquisition, normalized in terms of the current capital stock. Note that Equation (14) suppresses the geographical dimension of real estate prices. This amounts assuming that firms within each bin of productivity are equally distributed over the territory, allowing to consider the aggregate real estate price.

[19] This amounts assuming that firms are equally distributed over the territory, allowing to consider the aggregate real estate price. If these assumptions may seem strong, they are yet necessary to eliminate the real estate price in the aggregation formula, allowing us to derive weighting coefficients only as function of the real estate volumes. A more elaborate aggregation equation could be explored on French data, for which we have detailed geographical information. However, such an information is not be available on European data based on Compnet databases.

$$
\begin{aligned}
\frac{\partial I}{\partial REVal} &= \sum_j \widehat{\rho}_j \omega_j, \\
\text{with} \quad \omega_j &= \frac{RE_j^{vol}}{RE_T^{vol}}
\end{aligned}
$$

, i.e., Equation (9). For ω_j to be measured, we need to know the real estate volumes conditional on the labor productivity distribution. We can retrieve this information for France based on our firm database, but we cannot obtain the equivalent for the other European countries. Compnet data provides us with a solution yet, through its joint distribution dataset. Specifically, Compnet provides information on the distribution of (real) capital stock conditional on the decile of labor productivity, by country and year. We make use of this information to obtain a proxy value for the distribution ω_j (with $j = 10, 20, 30, 40, 50, 60, 70, 80, 90$) for all EU countries in the sample, as we detail now.

B.2 Implementing the empirical strategy on Compnet data

Compnet databse (6^{th} version) gives us a summary of the distribution of a various set of variables conditional on the percentile of the log of real labor productivity (as well as many other possible conditioning variables, but for reasons discussed in Section 3.2.2, we rely on labor productivity as performance variable). For our purpose, we are interested in the statistics for two variables, the real capital stock and the real labor productivity (in level). Notice that we use here the aggregate dataset, ie not starting from the macro sectors and rebuilding the aggregate without the real estate one. Would we start from information at the macro-sector, we would obtain statistics on labor productivity thresholds and the share of capital specific to each macro sector. Aggregating macro-sector statistics based on different percentiles would hence be meaningless. Further, it would not be consistent with our estimation on French firms, for which the distribution is estimated on the whole set of firms, indistinctive of the sector affiliation. Given the low weight of the real estate sector in total value-added or employment in our country sample (see Table A.11), it is not likely to bias the results much.

Obtaining the labor productivity threshold values We start explaining how we obtain the real labor productivity thresholds. The Compnet joint distribution provides us with statistics for each decile of the log real labor productivity distribution (by country-year), but it does not give us the threshold values of the real labor productivity associated to each percentile of the log real labor productivity, which we yet need to run our counterfactual estimation on French data. However, it provides us with the threshold values associated to the p1 and p99 percentiles of the real labor productivity (among other statistics), for each decile of log real labor productivity and for each year of observation. Given the monotonic relation between the real labor productivity in log and in level, we recover the (yearly) threshold value of the real labor productivity for each decile j of the log real labor productivity by assuming that it is the average value between the p99 value of the j^{th} percentile and the p1 value of the $j+1^{th}$ percentile. For each real labor productivity threshold value obtained, we then take the average value over the period covered by the Compnet dataset for the considered country (see Table A.10).

Obtaining the aggregation weights Consider now the second variable of interest, the capital stock. Per decile j of log labor productivity (for a given country/year), we have the mean value of the capital stock, K_j^{mean} and the number of firms (n_j) in the underlying population ("$rk-mean$" and "$rk-sum-weights$" respectively in the Compnet denomination), from which we can retrieve the total stock of capital through: $K_j = n_j K_j^{mean}$. Summing over all deciles j, we obtain the aggregate capital stock (for a given country/year) as $K_T = \sum_j K_j$. From this, we deduce the ratio that will give us the share of the capital stock owned by each decile j of log labor productivity in the aggregate capital stock. For a given country x:

$$\omega_x^j = \frac{K_x^j}{K_x^T}$$

To be consistent with our theoretical derivation of the aggregate elasticity (see Equation (9, where ω^j has no time-dimension), we consider the variable ω_x^j on average over the whole period.

Estimating the collateral channel on EU countries We then fuel the labor productivity threshold values, obtained on each European country into the French firms dataset. Specifically, we re-run our quantile regression by splitting the distribution of French firms based on the threshold values for real labor productivity obtained on each country of the Compnet sector. For each country x, and each bin j of the firm distribution, we thus get the estimated values of $\{\rho_x^j\}_{j=1}^{10}$. Aggregating these values given the relative weight of capital ω_x^j, we finally obtain an estimation of the strength of the aggregate collateral constraint in country j, based on Equation (11).

B.3 Distribution of performance indicators

In running our estimation of the financial accelerator in Europe, we retain labor productivity as the performance variable conditioning the heterogenous size of the collateral constraint. This relies on two main reasons, a comparability issue and an availability constraint, as we now detail.

First, the exercise faces a comparability issue between Compnet and our dataset. Transposing the country-specific thresholds values obtained through Compnet in our French data sample indeed raises a challenge of methodological order. For the transposition to be meaningful, it requires that the treatment of the performance variable is similar between Compnet and our own database (e.g, the choice of the deflator for real variables), so that it makes sense to estimate the semi-elasticity using the thresholds values *obtained on Compnet data* to partition the *French firm dataset* into the corresponding bins. We investigate this question carefully, using France as laboratory as it is the only one for which we can compare the two datasets. Specifically, we compare the threshold values associated to the different bins obtained on each set of data (Compnet and ours) for each of the performance variable considered. This is reported in the two last lines of Tables A.4 (real labor productivity) as well as for the other performance dimensions (Tables A.5 (for cash/asset), A.6 (real turnover) and A.7 (value-added), in Appendix C).

The good fit between both datasets in the French case in terms of real labor productivity justifies our choice of considering this specific dimension of firm performance to estimate the size of the financial accelerator in European countries (see the detailed discussion in Appendix C.

Table A.4: Real Labor Productivity distribution, European countries

	p10	p25	p50	p75	p90	p95	p99	mean
Belgium	20.04	31.81	46.42	68.59	103.26	135.89	236.19	56.59
Denmark	6.14	14.32	27.49	41.31	55.57	71.43	141.16	31.91
Spain	5.53	14.48	23.98	36.18	54.14	70.61	117.92	27.80
Italy	6.49	14.68	23.51	35.10	52.83	70.56	127.26	27.33
Netherlands	9.19	26.90	48.16	80.06	134.19	189.27	348.41	64.43
Portugal	-0.65	6.14	13.07	21.90	35.92	49.63	92.60	16.29
Sweden	11.30	21.31	33.54	50.75	75.72	93.63	145.94	40.02
France, Compnet data	12.72	23.88	36.93	55.85	83.01	108.81	206.53	45.03
France, BFF data	11.26	20.32	33.88	53.94	84.21	113.95	219.56	44.95

Notes: Authors' computations. Except for the last line, the thresholds values by decile come from the unconditional Compnet dataset by macro-sector, then re-built at the aggregate level excluding the real estate sector. Average values over the period by country. The last line reports our estimates of the real labor productivity thresholds distribution based on the French firms (BFF) datasat, averaged over the period.

In contrast, the difference in threshold values is substantial for real turnover and real value-added. This can be accounted for by the choice of the deflator from the nominal to the real dimension. Despite our effort to fit to what Compnet indicates as deflator[20], we fear that the difference remains too substantial for the comparison to be meaningful. This sensitivity to the deflator choice is likely to be alleviated when we consider variables in ratio, such as cash/asset or real labor productivity. The thresholds values obtained on French data indeed are much closer to those from Compnet for real labor productivity (Tables A.4 (Compnet unconditional data) and 3 (Compnet joint distribution data). This is not the case for the cash/asset variable though, whose threshold values are approximatively half (and in all cases systematically) lower in French data. On top of the deflator issue, this might be due to different definitions of the perimeter of cash or assets between ours' and Compnet's, the choice of elimination of outliers, etc. In any

[20]According to Compnet (2018), they use GDP deflator for turnover and sectoral value-added deflator for value added, base year 2005, then express the variables in PPP values using the 2005 US-€nominal exchange rate

case, this drives us to discard cash over assets as performance variable to condition the size of the financial accelerator across Europe. Real labor productivity remains as the relevant variable to perform this quantification.

The second reason behind this choice is due to data availability constraints for going back from semi-elasticities by bins up to the aggregate one. As exposed in Section 2, the aggregation key to convert the semi-elasticities by bin i of the performance variable Z to the aggregate one is the share of capital in the total capital stock, for each bin i in terms of the performance variable Z. This requires having information on the distribution of capital conditional of the quantiles of the performance variable Z, for each country in the European sample. Compnet fortunately provides us with this information, by deciles, but only for the (log) real labor productivity.

For these two reasons, we hence retain real labor productivity to recast the size of the financial accelerator across European countries.

Table A.5: Cash/Asset distribution, European countries

	p10	p25	p50	p75	p90	p95	p99	mean
Belgium	0.011	0.036	0.108	0.255	0.452	0.582	0.789	0.176
Denmark	0.023	0.053	0.098	0.156	0.237	0.318	0.479	0.120
Spain	0.010	0.031	0.100	0.259	0.491	0.653	0.925	0.183
Italy	0.002	0.010	0.049	0.157	0.325	0.452	0.706	0.114
Netherlands	0.011	0.043	0.148	0.342	0.562	0.696	0.903	0.224
Portugal	0.012	0.039	0.129	0.358	0.700	0.904	1.000	0.245
Sweden	0.016	0.078	0.235	0.461	0.687	0.796	0.946	0.296
France, Compnet	0.012	0.044	0.135	0.301	0.511	0.661	0.957	0.208
France, BFF	-0.050	0.020	0.072	0.144	0.255	0.356	0.634	0.084

Notes: Authors' calculations, from the Compnet unconditional dataset (6th version) (real estate sector excluded).

Table A.6: real Turnover distribution, European countries

	p10	p25	p50	p75	p90	p95	p99	mean
Belgium	98.51	193.86	434.30	1178.51	4078.68	8622.32	35468.74	2378.56
Denmark	27.56	57.15	161.24	554.49	1905.48	3893.87	16447.44	1105.30
Spain	33.74	80.21	190.94	449.76	1063.76	1908.92	7353.12	712.66
Italy	102.65	213.86	457.40	971.70	2074.22	3505.37	11420.30	1135.84
Netherlands	.	.	.	.	.	.	.	1540.63
Portugal	15.72	42.28	107.28	276.21	733.74	1400.18	5629.22	468.11
Sweden	34.03	73.53	161.29	380.24	938.17	1847.28	7923.52	540.50
France, Compnet	26.02	55.58	127.16	348.80	1012.57	2121.03	11203.14	760.98
France, BFF	131.57	266.24	601.43	1359.81	3462.84	6437.10	18077.31	1633.64

Notes: Authors' calculations, from the Compnet unconditional dataset (6th version) (real estate sector excluded).

Relative share of capital by decile of labor market productivity Tables A.8 and A.9 report the share of capital stock by decile of labor productivity, built from Compnet joint

Table A.7: real Value-Added distribution, European countries

	p10	p25	p50	p75	p90	p95	p99	mean
Belgium	21.15	49.82	110.41	241.13	526.18	936.94	3848.67	357.03
Denmark	5.72	14.76	50.56	177.80	581.71	1152.16	4577.68	335.42
Spain	3.28	21.31	59.46	135.88	278.08	460.66	1744.94	176.00
Italy	16.68	46.58	101.54	199.08	365.77	578.32	1843.11	201.26
Netherlands	16.24	58.83	147.09	310.98	645.18	1091.12	3841.60	387.95
Portugal	-3.63	6.05	27.61	72.99	173.33	314.55	1191.32	104.41
Sweden	14.85	33.00	70.67	150.79	321.08	574.13	2201.33	177.67
France, Compnet	0.76	14.00	42.80	121.76	334.35	656.89	2947.39	213.13
France, BFF	50.87	111.30	233.54	497.23	1110.73	1810.61	4463.52	503.93

Notes: Authors' calculations, from the Compnet unconditional dataset (6th version) (real estate sector excluded).

distribution dataset, for the sample of countries considered. For each decile, we display the share of capital stock considered on average over the period and the first year of observation. In all cases, the weights are very similar, showing strong inertia in the distribution of capital by labor productivity decile.

Table A.8: Relative share of capital, by decile on (log) real labor productivity (1)

Decile:	$< p10$		$p10 - p20$		$p20 - p30$		$p30 - p40$		$p40 - p50$	
	Year 0	Avg	Year 0	Avg	Year 0	Avg	Year 0	Avg	Year 0	Avg
Belgium	0.024	0.023	0.029	0.027	0.039	0.036	0.054	0.046	0.063	0.057
Denmark	0.004	0.006	0.008	0.012	0.018	0.019	0.029	0.028	0.053	0.042
France	0.027	0.026	0.038	0.034	0.055	0.048	0.070	0.064	0.089	0.081
Italy	0.029	0.030	0.028	0.025	0.031	0.028	0.036	0.032	0.046	0.038
Netherlands	0.024	0.032	0.038	0.043	0.048	0.057	0.084	0.072	0.110	0.091
Portugal	0.032	0.029	0.032	0.031	0.036	0.033	0.043	0.039	0.053	0.047
Spain	0.030	0.035	0.031	0.033	0.032	0.035	0.040	0.042	0.047	0.049
Sweden	0.003	0.009	0.007	0.010	0.007	0.012	0.008	0.019	0.011	0.019

Authors' calculations, from the Compnet joint conditional dataset (6th version). The conditioning variable is the log real labor productivity. The share of capital hold by each labor productivity decile is calculated on a yearly basis. In Column "Year 0" we report the distribution of capital shares the first year of observation in Compnet (by country). In the column "Avg", we report the distribution of capital shares on average over the period.

Table A.9: Relative share of capital, by decile on (log) real labor productivity (2)

Decile:	$50 - p60$		$p60 - p70$		$p70 - p80$		$p80 - p90$		$> p90$	
	Year 0	Avg	Year 0	Avg	Year 0	Avg	Year 0	Avg	Year 0	Avg
Belgium	0.075	0.069	0.088	0.082	0.097	0.100	0.135	0.128	0.397	0.431
Denmark	0.073	0.061	0.088	0.082	0.104	0.104	0.139	0.139	0.483	0.508
France	0.107	0.099	0.117	0.112	0.139	0.122	0.137	0.140	0.221	0.273
Italy	0.054	0.048	0.069	0.063	0.098	0.088	0.148	0.142	0.461	0.506
Netherlands	0.144	0.107		0.120	0.167	0.115	0.170	0.138	0.216	0.224
Portugal	0.071	0.062	0.090	0.082	0.120	0.114	0.168	0.165	0.356	0.398
Spain	0.060	0.061	0.078	0.077	0.099	0.099	0.136	0.138	0.447	0.432
Sweden	0.016	0.026	0.022	0.036	0.029	0.102	0.111	0.090	0.786	0.676

Authors' calculations, from the Compnet joint conditional dataset (6th version). The conditioning variable is the log real labor productivity.

C More on Compnet data

C.1 Time and country coverage

Table A.10: Coverage statistics on Compnet data

	Year		Nb of firms					
			Cash/asset			Real labor prod.		
Country	Initial	Final	Aggregate	Excl. RE sector	Ratio	Aggregate	Excl. RE sector	Ratio
Belgium	2004	2015	492646	462742	0.94	492583	462710	0.94
Denmark	2000	2015	196764	171802	0.87	196600	171727	0.87
Spain	2009	2015	2393011	2271467	0.95	2392729	2271322	0.95
France	2004	2014	2508970	2339589	0.93	2508574	2339297	0.93
Italy	2001	2014	3745545	3528336	0.94	3745509	3528336	0.94
Netherlands	2000	2014	606573	604945	1.00	606561	604935	1.00
Portugal	2006	2015	840141	811868	0.97	840007	811800	0.97
Sweden	2003	2015	566524	533102	0.94	566213	532802	0.94

Authors' calculations, from Compnet unconditional dataset (6th version), considering macrosector data.

Table A.11: Sectors share in value-added and employment, European countries

Sector	1	2	3	4	5	6	7	8	9
Share in VA									
Belgium	28.47	9.89	22.70	5.49	2.94	6.96	4.00	13.07	6.46
Denmark	30.24	9.61	19.42	8.69	3.38	10.55	5.04	8.22	4.86
France	28.67	10.71	23.21	5.03	4.41	5.98	2.86	12.71	6.41
Italy	26.29	12.70	25.23	4.78	4.20	3.29	5.90	13.68	3.94
Netherlands	24.14	12.97	24.31	7.53	4.26	6.62	2.74	13.18	6.26
Portugal	23.34	9.95	23.40	7.24	4.60	7.25	1.13	9.32	13.76
Spain	22.29	11.87	24.26	10.03	7.41	5.01	3.28	9.48	6.38
Sweden	21.48	10.34	20.78	5.61	3.12	8.08	11.33	16.37	5.21
Share in Employment									
Belgium	20.78	13.93	24.01	5.75	6.48	4.40	2.49	11.77	10.39
Denmark	25.26	11.87	23.32	8.48	5.54	5.78	3.52	9.68	6.55
France	20.44	14.84	24.09	5.68	6.93	4.21	3.75	12.67	7.38
Italy	22.54	14.22	26.90	4.71	7.42	2.54	3.06	13.00	5.60
Netherlands	19.62	14.01	24.84	7.40	6.06	4.94	1.75	12.32	10.42
Portugal	19.94	13.29	25.21	4.54	9.44	2.13	1.56	8.91	14.98
Spain	15.85	12.23	28.08	8.42	11.58	2.94	1.98	9.68	9.24
Sweden	21.69	13.58	22.17	6.69	5.29	6.69	5.26	15.62	6.95

Authors' calculations, from Compnet unconditional dataset (6th version), considering macrosector data. Results are average over the period covered by each country in the Compnet database. Sector: 1, Manufacturing; 2, Construction; 3, Wholesale and retail trade, repair of motor vehicles and motorcycles; 4, Transportation and storage; 5, Accommodation and food service activities; 6, Information and communication; 7, Real estate activities; 8, Professional scientific and technical activities; 9, administrative and support service activities.

D Additional Regression Tables

D.1 French data: More on the average effect

Table A.12: Determinants of Real Estate ownership

	(1) RE value	(2) RE ownership (1 if RE>0)
2nd quintile of asset	0.084^a	0.13^a
	(0.00064)	(0.00048)
3nd quintile of asset	0.17^a	0.18^a
	(0.00063)	(0.00049)
4nd quintile of asset	0.084^a	0.082^a
	(0.00064)	(0.00049)
5nd quintile of asset	0.19^a	0.18^a
	(0.0007)	(0.00053)
2nd quintile of ROA	0.21^a	0.28^a
	(0.00054)	(0.00039)
3nd quintile of ROA	0.14^a	0.23^a
	(0.00056)	(0.00042)
4nd quintile of ROA	0.012^a	0.042^a
	(0.00054)	(0.0004)
5nd quintile of ROA	$-.04^a$	$-.04^a$
	(0.00053)	(0.00039)
2nd quintile of age	0.032^a	$-.026^a$
	(0.00047)	(0.00035)
3nd quintile of age	0.11^a	0.029^a
	(0.00053)	(0.0004)
4nd quintile of age	0.2^a	0.081^a
	(0.00056)	(0.00042)
5nd quintile of age	0.35^a	0.17^a
	(0.00061)	(0.00047)
Observations	9,307,373	11,717,067
Adjusted R^2	0.12	0.17

Standard errors in parentheses. Sector and strate fixed effects included. The firm's position in the distribution of ROA, asset and age assessed the first year of the firm's observation. $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$

Determinants of Real Estate ownership

IV estimation: First stage results Table A.13 reports the results for the estimation of the first-stage equation 5 for our first main specification. As expected, the coefficient attached to the bartik instrument is positive and significant, in line with Chaney et al. (2012).

Table A.13: First stage estimates

	(1)	(2)	(3)	(4)
Dependent variable	Flat price		House price	
Bartik	0.0053^a	0.0053^a	$.0017^a$	0.0017^a
	(.0009)	(.0009)	(0.0006)	(0.0006)
Urban Area FE	No	Yes	No	Yes
Obs.	23,709	23,709	23,533	23,533
Adj. R^2	0.99	0.99	0.99	0.99

Regression run at the strate-year level. Strate- and year-FE always included. Standard errors in parenthesis. ^{c} $p < 0.1$, ^{b} $p < 0.05$, ^{a} $p < 0.01$.