The Channels of Amplification: Dissecting the Credit Boom that led to the Global Financial Crisis*

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Abstract

An unprecedented credit boom that began in the early 2000s was a central cause behind the global financial crisis. Both a housing boom and a relaxation of lending constraints that unlocked an aggressive channeling of funds to the mortgage market (the financial intermediary channel) were key determinants of the credit boom. However, little is known about the relative roles played by each factor. This paper provides a novel empirical strategy to shed light on this issue. Building on two natural experiments identified in the literature, I show that both channels played a significant role in amplifying the rise in credit. In the preferred specification, the housing channel accounts for 51% of the observed amplification. Both the amount of amplification and the proportion explained by the housing channel are larger (66%) in areas with more inelastic land supply. Regions with very elastic land supply still display significant regional credit multipliers thanks to the financial intermediary channel, which accounts for 71% of the effects. Thus, both channels are essential to understand the drastic and geographically pervasive growth of credit during this episode.

Keywords: Causal mediation analysis, credit multipliers, credit boom, housing boom, banks, shadow banks

JEL classification: G21, G28, E44, C23.

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1 Introduction

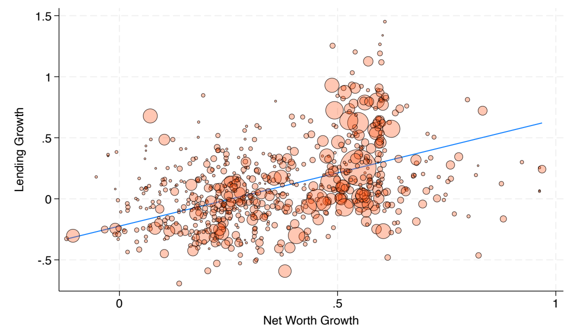
The global financial crisis (GFC) that the U.S. and the major developed economies went through fifteen years ago spurred an immense amount of research directed towards understanding the causes and consequences of this episode. This is comprehensible given the severe recession that followed, and the long term consequences on economic growth. Even though there are still some debates on the specifics of the causes behind the GFC, a consensus has emerged on two key factors that shaped the events that followed.[1] The first one is the buildup of fragility in the financial sector, which took the form of excessive leverage, particularly among broker-dealers and non-banks, and the increased reliance on flighty short-term funding subject to runs. The second one is an unprecedented credit boom, particularly mortgage boom, in the household sector that began in the early 2000s.

The focus in this paper is on the latter. Although the exact ultimate causes behind the credit boom are also still debated, by now we have a good understanding of its main features and the mechanisms behind it. To illustrate the magnitude of the boom, it suffices to point that mortgage debt doubled in the six years before the crisis, reaching 72% of GDP by 2007.[2] Moreover, the credit boom was widespread, prevalent in all income groups, and it was not offset by reductions in other household debt.[3] In terms of its inner workings, two crucial phenomena went hand in hand with the credit boom. The first one was a housing boom: real house prices rose between 40% and 70% during the 2000-2006 period, and the ratio of residential mortgages to the value of residential real estate remained roughly constant until 2006.[4] Second, there was a relaxation in lending constraints that unlocked an aggressive channeling of funds towards the residential mortgage sector. Lending standards loosened in the years before the crisis, deteriorating borrower quality significantly, and the explosion of securitization that began in the late 1990s took a violent turn with the expansion of the private-label securitization market.[5] Real mortgage rates declined by between 2% to 3%, mortgage spreads fell.[6] Thus, increased quantities along with the lower spreads suggest an expansion in credit supply.

Figure 1, although purely descriptive, perfectly illustrates the forces at play. On its left

[1] See, among others, Bernanke (2018); Justiniano, Primiceri and Tambalotti (2019); Aikman, Bridges, Kashyap and Siegert (2019); Mian, Sufi and Verner (2017).
[2] See, e.g., Aikman et al. (2019).
[3] See, e.g., Adelino et al. (2016, 2018b).
[4] See, e.g., Justiniano et al. (2019).
[5] In particular, from the $600 million increase in the flow of mortgage originations in 2006 relative to 2002, roughly 80% were mortgages originated for the private-label securitization market (PLS market). See, e.g., Mian and Sufi (2021).
[6] See, e.g., Justiniano et al. (2022).

(a) House Prices



(b) Net Worth

Figure 1: Lending against house prices (panel a) and net worth (panel b).
The figure shows the relationship between lending growth and house price growth (panel a) and between lending growth and net worth growth (panel b) during the 2002-2005 period at the county level. The blue line corresponds to a regression with county population in 2002 as weights. Circle size indicates the county's population as of 2002.

panel, it plots lending growth against house price growth at the county level during the 2002-2005 period. As we would have expected, there is a very strong co-movement between house prices and mortgage lending in the cross-section of U.S. counties during the period. On the other hand, although the relaxation of credit constraints is clear from a conceptual standpoint, it is harder to isolate a single variable that would capture this shift. However, it is clear that the combined lending capacity of the lenders in a given county played a major role, as it is directly linked to the expansion in credit supply experienced during the period. Hence, panel b in Figure 1 plots lending growth against lenders' net worth growth at the county level during 2002-2005.[7] As expected, there is also a strong positive co-movement between lending growth and lenders' lending capacity in the cross-section of counties.

Although it is clear that both phenomena, the housing boom and the relaxation of credit constraints, played a very important role, their relative contributions are much less clear. The reason it is hard to asses their relative roles is that in Figure 1 many things are happening simultaneously. Understanding the relative roles played by each factor is of utmost importance not only because it would help us understand better the events that led to the GFC, but also because it is critical to design policies and regulation that can help us prevent events like these from happening again. Up to this point, the literature has focused intensively on the ultimate causes behind the credit boom. However, consistent both with standard narratives around the boom and the theoretical models proposed to explain it,[8]

[7] In the figure, a county's net worth growth is defined as the deposit weighted average of the equity growth rates of the banks operating in the county. For a detailed discussion on the advantages and disadvanatges of this measure, as well as results under alternative ones, see Sections 4 and 5.

[8] These models, in turn, build on standard models that examine the relationship between the financial sector and the macroeconomy.

Mian, Sarto and Sufi (2023) recently showed that credit markets experienced a significant amount of amplification during the episode (with credit multipliers that can quadruple the partial equilibrium effects). This means that the gains from shifting the focus to the amplification process that took place are outstanding. Not only does this process likely explains most of the rise in credit the economy went through, but also, absent the incontestable evidence on the initial impulse to the system, knowing how it likely propagated gives the necessary tools to design policies that can restrain that process and avoid future events of the sort.

This paper is the first to put the focus, methodologically and empirically, on dissecting this amplification process. Building on Mian, Sarto and Sufi (2023), it presents a novel empirical strategy to make two contributions on this front. First, it presents 2SLS estimates of the conditional elasticities that lie behind the relationships in Figure 1. Under the preferred specification, the conditional elasticity of house prices is 0.75, and that of net worth is 0.5. This means that, holding net worth fixed, a 1% increase in house prices generates a 0.75% increase in lending, and that, holding house prices fixed, increasing the net worth of the lenders in the county by 1% increases lending by 0.5%. These numbers contrast with OLS estimates of 1.22 and 0.27 for house prices and net worth, respectively. Thus, OLS significantly underestimates the effect of net worth, and overestimates the effect of house prices. This is consistent with a data generating process in which lending affects both house prices and lenders' net worth, but with a larger effect on the former. Given that many of the lenders are large, operate nationally, and the mortgage market is a fraction of their operations, it is indeed plausible that mortgage lending has a stronger effect on house prices. The 2SLS estimates removes this source of bias, leading to increased estimates for net worth, and smaller estimates for house prices.

The second contribution is to decompose the regional effects of two natural experiments identified in the literature between the effects coming through house prices, the "housing channel", and the effects coming from lenders' net worth, the "financial intermediary channel" (FI channel). The first credit supply shock I exploit is from Mian and Sufi (2021), and is tied to the sudden surge in the PLS market starting in 2003. The second shock comes from Di Maggio and Kermani (2017), and is tied to the federal preemption of national banks from local antipredatory-lending laws. These decompositions enable us to go beyond the conditional elasticities of house prices and net worth, and look at how two identified credit supply shocks propagated through the system, allowing us to see how the shocks impacted lending through the two channels. Moreover, the fact that the results align so well for two different natural experiments, which exploit such different sources of variation, significantly increases the confidence in the decompositions.

Mian and Sufi (2021) showed that lenders relying more heavily on non-core deposit financing ("high NCL lenders") were able to expand their lending more aggressively during the PLS surge. Di Maggio and Kermani (2017), in turn, showed that national banks were able to increase their lending relatively more in states with antipredatory-lending laws (APL laws) starting in 2004, when the OCC enacted a preemption ruled that exempted them and their mortgage subsidiaries from the APL laws. Using a novel methodology, Mian, Sarto and Sufi (2023) separated the partial equilibrium effect of the shocks at the lender level, from the regional effect that accounts for the spillovers that amplified the initial impact in general equilibrium. In the study, they estimated a large amount of amplification at the regional level for both shocks. These amplification effects, that arise between the lender and regional levels, are precisely where house prices and lending constraints come into play. House price increases relax the collateral constraints of borrowers whose lenders were unaffected by the shock, increasing their borrowing capacity. Relaxed lending constraints allow lenders initially unaffected by the shock to also extend more credit to their borrowers. These "second round" effects accumulate on top of the PE effect, and place the regional effects above the latter.

Under my preferred specification, the housing channel accounts for 51% of the amplification effects, and the remaining 49% belongs to the FI channel. However, both the amount of amplification and the share coming from the housing channel increase in regions with very inelastic housing supplies, which is reasonable since more inelastic supplies lead to larger house price increases and larger relaxations of the collateral constraints.[9] In these regions the housing channel accounts for 66% of the effects, compared to 29% in areas with very high housing supply elasticities. In particular, this means that, in regions with very elastic supplies, 71% of the effects are coming from the FI channel. This explains why there still are significant amounts of amplification in those areas, even though housing plays a lesser role.[10]

The empirical strategy is grounded on a model in which house prices and lending constraints amplify the effects of lender-level credit supply shocks. The model is inspired by Justiniano, Primiceri and Tambalotti (2019) and builds on Mian, Sarto and Sufi (2023) to create a role for lenders' net worth. In the model, higher house prices relax the collateral constraints borrowers face, and increases in lenders' net worth also prompt them to accept lower down-payments. Both forces shape the amplification effects. Thus, the model motivates an empirical strategy in which the spillovers at the regional level are being transmitted

[9] See Mian, Sarto and Sufi (2023) for further details.

[10] Note that even if the FI channel played no role, we would not expect zero amplification in those areas based on the housing channel alone, because as long as supplies are not perfectly elastic, there is going to be amplification through this channel.

through the housing and FI channels.

The key identification assumption that operationalizes the empirical strategy is an asymmetry between the two channels with respect to which shocks are relevant for them. The asymmetry lies in the structure of the housing market vis-à-vis the structure of bank and non-bank networks of operations. Housing markets are geographically segmented, whereas (most) lenders operate in multiple regions simultaneously; multiple regions that can be as far apart as New York City is from San Francisco. This asymmetry suggests that, for a given county, shocks to nearby counties are probably the relevant shocks for its housing market, while shocks to the deposit or loan networks of the lenders operating in the county are the relevant ones for their net worth. In other words, at the regional level, credit supply shocks in SF county are not relevant for NY county's housing market, but they are for its lenders' net worth if they operate in both counties. However, shocks in Kings County, right next to NY county, are almost surely relevant for its housing market.

In the empirical results I show that this is indeed the case. Using county-level specifications I show that for a given region, once one controls for the shocks to nearby regions, shocks to the deposit network of its lenders have no impact on its house prices. Conversely, I show that once one controls for the shocks to the deposit network of its lenders, shocks to nearby regions have no effect on their net worth. These results are important for two reasons. First, because if we want to identify two channels, we need at least two exogenous sources of variation that are distinctively relevant for each one. Second, because to identify both channels, in addition to the 2SLS estimates described above, we need to accurately measure the impact of the shocks on both house prices and net worth.

There are three main threats to the strategy in this paper. The first one is related to the choice of the network for the net worth effects. On this front, I show that as long as one captures the correct set of connections across regions, the specific weight assigned to the links in the network are irrelevant asymptotically. Given that the empirical results rely on county level data this result heavily alleviates any concerns about network misspecification. Regardless, I also show results that rely on the deposit network of the banks in the region, as well as the mortgage loan networks of all lenders in the region.

The second main concern is related to the channels at play: how can we be sure the housing channel and the FI channel are the only ones at play? Because the empirical strategy naturally provides over-identifying restrictions, I show that the Sargan-Hansen J test fails to reject the null even in lender level specifications, which have around $50,000$ observations in the case of the Mian and Sufi (2021) credit supply shock and around $25,000$ observations in the Di Maggio and Kermani (2017) setup. This is strong evidence that we are indeed capturing all the relevant channels of amplification.

The third main concern is a standard one in any IV setup, and in this case takes the form of worrying that the credit supply shock could be contaminated with a demand component. I first present simulations that show that, because these demand shocks are likely to bias upwards both channels, the breakdown that I estimate between them, being a ratio, would be very mildly affected. Then, for both credit supply shocks, I show that the partial equilibrium effects estimated in Mian, Sarto and Sufi (2023), which are robust to demand shocks at the regional level, are essentially unchanged when all the amplification is attributed to the housing and FI channel. This is strong evidence that both credit supply shocks are not picking up demand components. Finally, I also present a battery of robustness checks related to less pressing concerns.

Relation to the literature This paper is related to two strands of the literature. First, it is tightly connected with the literature on the credit boom that led to the global financial crisis.[11] On the conceptual side, it is closely related to Justiniano, Primiceri and Tambalotti (2019), from which I take a general framework to augment the model in Mian, Sarto and Sufi (2023) and later design the empirical strategy. Because of this it is also related to Justiniano, Primiceri and Tambalotti (2022). On the empirical side it is closely linked to Mian and Sufi (2021) and Di Maggio and Kermani (2017), from which I take the primitive inputs to the empirical strategy.

At a higher level, in addition to documenting many important patterns and mechanisms behind the boom-bust cycle, from which this paper benefits substantially, this literature also focused intensively on trying to isolate the initial, primitive, shock that triggered the boom. Even though this is a high priority objective, in this paper I take a different route to addressing the credit boom. Mian, Sarto and Sufi (2023) developed a novel approach to measure the amplification in credit markets and found, in two episodes during the boom, a substantial amount of amplification. Thus, in this paper, I build on that insight and approach to instead shift the focus to understanding and dissecting the amplification during this time. Given that the amplification during this episode was so large, focusing on it becomes of great relevance, and, even if future research pins down unequivocally the initial impulse, the analysis in this study will be informative about its propagation through the system and

[11] A non-exhaustive list includes Adelino et al. (2016, 2018a,b); Agarwal et al. (2014); Albanesi et al. (2022); Ben-David (2011); Chaney et al. (2012); Chinco and Mayer (2015); Chodorow-Reich (2014); Di Maggio and Kermani (2017); Favara and Imbs (2015); Foote et al. (2021); Gao et al. (2020); Garmaise (2015); Greenstone et al. (2020); Griffin and Maturana (2016); Griffin (2021); Griffin et al. (2021); Herbst et al. (2024); Huber (2018); Ivashina and Scharfstein (2010); Jiang et al. (2014); Jordà et al. (2013); Kaplan et al. (2020); Keys et al. (2010, 2012); Landvoigt et al. (2015); Landvoigt (2017); Mian et al. (2013); Mian and Sufi (2009, 2011, 2014, 2021); Mian et al. (2010, 2015); Nadauld and Sherlund (2013); Piskorski et al. (2015); Purnanandam (2011); Rajan et al. (2015).

a substantial amount of its final effects. In this respect, the fact that the analysis for the two natural experiments exploited in this paper give answers that align so well with each other is very reassuring.

This paper is also related to the recent literature that exploits regional variation to estimate elasticities at higher levels of aggregation. In particular, it shares the emphasis on reduced-form techniques present in Gertler and Gilchrist (2019), Gabaix and Koijen (2021), Mian, Sarto and Sufi (2023), Berg et al. (2021), Huber (2022), and Sarto (2024). In this dimension it is tightly connected to Mian, Sarto and Sufi (2023). That study presented a novel approach to estimate amplification in credit markets. In this paper, I build on that approach and go one step further to decompose the amplification between the two main channels that the literature has emphasized for the credit boom. Doing so requires estimating the conditional elasticities of each channel as well, so the two main results in this paper are an outcome of this next step.

2 A Model of Amplification through House Prices and Lending Constraints

The model in this section builds on Mian, Sarto and Sufi (2023) and is inspired in the work of Justiniano, Primiceri and Tambalotti (2019). The main difference from the model in Mian, Sarto and Sufi (2023) is that I introduce a role for increases in the net worth of banks to alleviate the credit constraint faced by entrepreneurs.

2.1 Environment

There are two dates, $t = 0, 1$ and $i = 1, ..., I$ locations. I interpret the different locations as belonging to the same unique region, but the model can easily be extended to feature a discrete number of regions, with I locations in each one, as in Mian, Sarto and Sufi (2023). Since the focus in this section is on the amplification channels I simplify the setup to a single region. In each location, there is one entrepreneur (E) and one bank (B). There are three goods in the economy: a tradable consumption good, "fruit", which is non-durable, and two durable goods, "land" and "machines". The markets for the three goods are competitive, so both banks and entrepreneurs take prices as given.

Preferences, Technologies and Endowments Banks' preferences are given by $U_i^B = c_{i0}^B + c_{i1}^B$, and entrepreneurs' preferences by $U_i^E = c_{i1}^E$, where $c_{i1}^E, c_{i0}^B, c_{i1}^B \geq 0$. Entrepreneurs produce according to $f_E\left(d_{it}^E, m_{it}^E\right) = A_{it}\min\left\{d_{it}^E, m_{it}^E/\varsigma_{it}, F_{it}^E/\chi_{it}^E\right\}$, where d_{it}^E is land of entrepreneur i in period t, m_{it}^E denotes machines, and F_{it}^E is fruit used for the land. That is, to produce $A_{it}d_{it}^E$ units of the consumption good in period t, entrepreneurs have to combine exactly d_{it}^E units of land, $d_{it}^E\varsigma_{it}$ machines and $d_{it}^E\chi_{it}^E$ units of fruit. Banks produce according to an inferior decreasing returns technology given by $f_B\left(d_{it}^B\right) = \varrho_{it}^d ln\left(\min\left\{d_{it}^B, F_{it}^B/\chi_{it}^B\right\}\right) + \varrho_{it}^m ln\left(m_{it}^B\right)$.[12]

There are total amounts $\overline{D}$ and $\overline{M}$ of productive land and machines, respectively, which are distributed across both banks and entrepreneurs. The initial distributions of land and machines satisfy $\sum_{i=1}^I\left\{d_{i0}^E + d_{i0}^B\right\} = \overline{D}$ and $\sum_{i=1}^I\left\{m_{i0}^E + m_{i0}^B\right\} = \overline{M}$. Final consumption goods can be turned by anyone into productive land and machines one for one, but the opposite is not feasible. Finally, banks are endowed with an amount e of consumption goods in both periods (deep pockets).

Credit Markets Each bank can only lend to the entrepreneur in its own location. Moreover, in each bank-entrepreneur relationship, the entrepreneur has all the bargaining power. At $t = 0$, entrepreneurs offer financial contracts to banks. A financial contract is $\left\{l_{i1}, l_{i1}^R\right\}$ where l_{i1} is the loan taken by the entrepreneur at $t = 0$ and l_{i1}^R is the repayment at $t = 1$. I assume entrepreneurs also start with some debt l_{i0} that they must repay in full at $t = 0$ if they wish to take on new loans. This initial debt level implies that entrepreneurs start period $t = 0$ with leverage, and this will be one of the key elements I will emphasize when analyzing the behavior of the model.

The entrepreneurs budget constraints are:

$$\left(\chi_{i1}^E + q^d + q^m\varsigma_{i1}\right)d_{i1}^E + l_{i0} \leq \left(A_{i0} + q^d + q^m\varsigma_{i0}\right)d_{i0}^E + l_{i1}$$
$$c_{i1}^E \leq A_{i1}d_{i1}^E - l_{i1}^R,$$

where q^d is the price of a unit of land in $t = 0$ and q^m is the price of machines. Note that, since period $t = 1$ is the last period, land and machines have no value, their price is zero, so we do not need to index q^d and q^m by time.

As in Mian, Sarto and Sufi (2023) I assume that the amount of lending is subject to a collateral constraint in the spirit of Kiyotaki and Moore (1997). The constraint takes the form:

$$l_{i1}^R \leq \theta_i\left(W_0\right)A_{i1}d_{i1}^E, \tag{1}$$

[12] The separability of land and fruit from machines in banks' production function is just for simplicity in characterizing the equilibrium, none of the properties we are interested in hinge on this.

where:

$$\theta_i(W_0) = \left[\overline{\theta}_i + \frac{e^{-W_0}}{W_0}\right]^{-\frac{1}{\psi_i}},$$

and W_0 is the average marked-to-market value of banks' (book) assets, that is $W_0 = q^d d_0^B + q^m m_0^B + l_0$, with $d_0^B = \frac{1}{I}\sum_i d_{i0}^B$ and similarly for m_0^B and l_0. The function $\theta_i(.)$ is positive, increasing, and satisfies $\lim_{W_0 \to 0} \theta_i(W_0) = 0$ and $\lim_{W_0 \to \infty} \theta_i(W_0) = \overline{\theta}_i^{-1/\psi_i}$, where I take $\overline{\theta}_i^{-1/\psi_i} < 1$. That is, $\theta_i(.)$ is effectively a fraction that increases with the size of banks' balance sheets. The higher their initial assets, the laxer the credit constraint. Given the interpretation of the I locations as belonging to the same region of a multi-region economy, this feature captures, intuitively, the fact that in reality banks might accept lower down payments when the lending capacity of lenders in their same region increases because, e.g., they could sell their loans more easily in case of need (Justiniano et al., 2019).[13] Thus, there are two ways the credit constraint can be alleviated for entrepreneurs in (1). Either they become more productive, so that $A_{i1}d_{i1}^E$ increases, or the banks in their region become larger on average, increasing W_0 and $\theta_i(.)$ with it.

Market Clearing Market clearing requires that supply and demand of land and machines are equated, i.e., $\sum_i \left\{d_{i1}^E + d_{i1}^B\right\} = \overline{D} + I^d$ and $\sum_i \left\{m_{i1}^E + m_{i1}^B\right\} = \overline{M} + I^m$, where $I^d \geq 0$ is aggregate production of land, and $I^m \geq 0$ is aggregate production of machines.

2.2 Equilibrium Characterization

The following proposition shows existence and uniqueness, and characterizes the patterns of amplification of a credit supply shock in a sense that is made precise. In addition to Assumptions 4 and 5, which are described in detail in Appendix B.1, I impose some parametric restrictions to make sure aggregate demands for the assets are downward sloping and the equilibrium is interior. The shock I consider is a small increase in ψ_i in (1), which relaxes slightly that constraint. To simplify the exposition I consider an economy with $\psi_i = \psi\ (\forall i)$, which is completely inessential. I also denote by $l_{i1}^*\left(\psi, q^d, W_0\right)$ the partial equilibrium value of lending in location i, l_{i1}, for arbitrary values of land and banks' balance sheets, q^d and W_0 respectively. All the details can be found in the proof in Appendix A.

Proposition 1. *A credit constrained equilibrium exists and is unique. Moreover, the equilibrium*

[13] The connection between lending capacity and collateral constraints is a departure from the standard version of Kiyotaki and Moore (1997).

exhibits amplification effects through the price of land and banks' balance sheets in the sense that:

$$\partial l^*_{i1}/\partial\psi > 0 \tag{2}$$

$$dl^*_{i1}/d\psi - \partial l^*_{i1}/\partial\psi = \left(\partial l^*_{i1}/\partial q^d\right)\left(dq^d/d\psi\right) + \left(\partial l^*_{i1}/\partial W_0\right)\left(dW_0/d\psi\right) > 0, \tag{3}$$

and:

$$\partial l^*_{i1}/\partial q^d,\ \ dq^d/d\psi,\ \ \partial l^*_{i1}/\partial W_0,\ \ dW_0/d\psi > 0. \tag{4}$$

Proposition 1 shows that the partial equilibrium effect of ψ is positive (equation (2)), and that the general equilibrium multiplier raises the final effect of the shock above its partial equilibrium effect (equation (3)). These two pieces combined mean that the initial shock is *amplified* in general equilibrium.[14] Equation (3) says that land prices and the size of banks' balance sheets are the drivers of this amplification, and equation (4) says both channels contribute to amplify the initial shock, as opposed to a case in which one of the channels might amplify the initial shock and the other one dampen it (with amplification overall). That is, the shock increases lending on impact, and this additional borrowing triggers an increase in land prices and banks's balance sheets which themselves trigger further increases in credit. The reason for this feedback is that increases in land prices and banks' balance sheets increase entrepreneurs' net worth proportionally more than the increases in the price of the assets, and the latter also prompts banks to accept lower down payments. Both elements then contribute to increase borrowing above the initial impact of the shock.

3 Decomposing the Credit Multiplier

The results in the previous section summarize the conceptual framework that explains the amplification coming from the housing and financial intermediary channels during the credit boom. Using two different natural experiments that isolated credit supply shocks during this episode (Di Maggio and Kermani, 2017; Mian and Sufi, 2021), Mian, Sarto and Sufi (2023) estimated a sizable amount of amplification overall. In this section I put forward a novel empirical strategy that builds on Mian, Sarto and Sufi (2023) and the conceptual framework of the previous section to decompose this amplification, and answer the question of how much did each channel contribute to it.

[14] Whenever the partial equilibrium effect has the opposite sign of the multiplier, we would say there is *dampening*.

3.1 Setup

The point of departure for the analysis is a system of equations that is comprised of a log-linear version of the partial equilibrium function in the previous section, $l^*_{i1}\left(\psi, q^d, W_0\right)$, along with (log-linear) equilibrium equations for house prices and lenders' net worth:

$$y_{in} = \beta_{pe} z_{in} + \gamma_P P_n + \gamma_W W_n + \varepsilon_{in} \tag{5}$$

$$P_n = \phi_P \overline{z}_n + v_n^P \tag{6}$$

$$W_n = \sum_{b \in B_n} \omega_{nb} W_b \tag{7}$$

$$W_b = \phi_W \sum_{c \in C_b} l_{cb} \overline{z}_c + v_b^W, \tag{8}$$

where y_{in} is lending growth of lender i in region n from period $t-1$ to t, P_n is house price growth in region n, and W_n is lenders' net worth growth, or some measure of growth in lenders' lending capacity, in region n. There are $i = 1, ..., I$ lenders per region with $n = 1, ..., N$ regions. For simplicity, I assume $t = 0, 1$, i.e. there are only two periods ($T = 2$) and thus, in terms of the notation of the model in the previous section, $y_{in} = \Delta log\left(l_{int}\right) = log\left(l_{in1}\right) - log\left(l_{in0}\right)$ (where I now make explicit the region n in the notation). The identification arguments that follow apply to setups with longer panels ($T > 2$), but because the time dimension is not important for them I simplify the notation and suppress the dependance on t. Moreover, because the system is already written in terms of first differences and I assume $T = 2$, I omit any panel fixed effects, but those are allowed in the model in levels that lies behind (5)-(8). Similarly, the model includes time fixed effects, but to simplify the exposition regarding identification I take (5)-(8) as the system remaining after partialing them out. In particular, the shocks ε_{in}, v_n^P, and v_b^W are mean-zero.

Moving forward with the other variables in the system, z_{in} represents the credit supply shock, such as the ones identified in Di Maggio and Kermani (2017) and Mian and Sufi (2021). More generally, all the arguments that follow hold for any randomized source of variation or exogenous conditional on observables. $\overline{z}_n = \frac{1}{I}\sum_i z_{in}$ is the within-region average of the z_{in}s and, in general, I will use $\overline{x}_n = \frac{1}{I}\sum_i x_{in}$ for an arbitrary variable x_{in}.[15] Moreover, to make the notation lighter, I always omit the upper and lower bounds of summations when summing across all units, e.g. $\sum_i x_{in} = \sum_{i=1}^{I} x_{in}$.

Before diving into the specifics of equations (6)-(8) it is useful to discuss the general motivation for a system such as (5)-(8). The motivation comes from the log-linearization of

[15] The fact that equations (6)-(8) are functions of simple averages of the z_{in}s is completely inessential, they could be replaced by an arbitrary weighted average.

the model in the previous section around the credit constrained equilibrium of Proposition 1. It is straightforward to show that such log-linearization gives a system very similar to (5)-(8).[16] However, depending on the assumptions about the market structures of the relevant general equilibrium objects, the shocks that enter equations (6)-(8) are going to differ.

Equation (6) says house prices in region n depend on the shocks to the lenders of region n. Equation (7), in turn, says that the relevant measure of lenders' lending capacity in region n is a weighted average of the net worths of the lenders operating in region n, where ω_{nb} is the share of lender b in region n, and B_n is the set of lenders operating in region n. For the moment, the only relevant features on the ω_{nb}s are that they are weights, i.e. they satisfy $\omega_{nb} > 0$ and $\sum_{b \in B_n} \omega_{nb} = 1$ $(\forall n)$, and that they are observed. Below I discuss different specifications for them, and I also present results that show what happens if we misspecify them, when does it matter and how. I should note though, at this point, that for the identification arguments the ω_{nb}s need not be weights; some could be negative and they do not need to add up to one. However, because of the structure of the most commonly used models in macro and macro-finance, the log-linearizations will feature ω_{nb}s that have these properties, so I focus on this case. Finally, equation (8) says that lender's b net worth depends on a weighted average of the shocks to all of the regions in which it operates: C_b is the set of regions in which lender b operates, and l_{cb} is the weight that region c has in lender b's net worth. The same logic of the weights ω_{nb}s applies to the l_{cb}s.

I postpone the discussion of the reasons for the specifics of equations (6) and (8) until Section 3.4 which delves into identification and estimation. These arguments are not needed in the next section, in which I define and compare different credit multipliers.

3.2 Local vs Global Regional Multipliers

In this section I characterize three causal effects of interest in system (5)-(8). At this stage of the analysis, I view (5)-(8) as a structural equations model, i.e. a collection of functional relations along with shocks that satisfy some orthogonality conditions. The structural equations are derived from a model such as the one in Section 2, by log-linearizing the model around the credit constrained equilibrium. Because of this, the coefficients in system (5)-(8) are going to be functions of the underlying fundamentals of the economy that is generating the data (the curvature of the production function, parameters governing preferences, etc). Thus, by defining the causal effects of interest explicitly in terms of the coefficients in system (5)-(8) we make sure that if we are able to estimate them precisely, our estimates will be robust to many different models such as the one in Section 2 generating the data. That is,

[16] For a more detailed discussion of this point along with concrete examples see, e.g., Mian et al. (2023); Sarto (2024).

as long as the general structure of the log-linearized model fits in (5)-(8) our estimates will be valid, regardless of the specifics of the production function, or the collateral constraint, etc.[17]

However, in this section I am not concerned with estimating anything, yet; I tackle this issue below in Section 3.4. At this stage I view, for example equation (5), as a random mapping that details how the lending growth y_{in} would vary for different, hypothetical, levels of the credit supply shock, house prices and lenders' net worth in region n, regardless of whether those are the observed values in region n or not. The mapping is random because of the shock ε_{in}. The only thing we know at this stage is that the shock ε_{in} is not a function of those hypothetical values. In particular, this does not mean that the sampling process could be such that, e.g., v_n^P is correlated with ε_{in}, and hence applying OLS to (5) using the observed values of the variables would fail to recover $(\beta_{pe}, \gamma_P, \gamma_W)$. I deal with these concerns when I present the identification and estimation results below.

The three causal effects of interest are the partial equilibrium effect of the credit supply shocks, and two regional multipliers. The latter capture different parts of the spillovers transmitted through house prices and lenders' net worth. In order to define them precisely, let us first define the partial equilibrium effect of the credit supply shock. From equation (5) we can isolate the deterministic mapping going from the (hypothetical) credit supply shock, house prices and lenders' net worth to lending and define:

$$h_{pe}(z_{in}, P_n, W_n) = \beta_{pe} z_{in} + \gamma_P P_n + \gamma_W W_n.$$

The partial equilibrium effect is then given by $\partial h_{pe} / \partial z_{in} = \beta_{pe}$. That is, β_{pe} captures the partial equilibrium effect of the credit supply shock because it holds constant the general equilibrium objects at the regional level.[18] This is the same definition as in Mian, Sarto and Sufi (2023).

The first multiplier of interest at the regional level is one in which we allow house prices and lenders' net worth in the region to change only because of the credit supply shocks in region n. The second multiplier of interest is one in which we allow both regional equilibrium objects to change because of all the credit supply shocks, not only those of region n.

To define them precisely, let us plug in equations (6)-(8) in (5) and aggregate to the

[17] See Mian et al. (2023); Sarto (2024) for further discussion of this point.

[18] We are also holding constant all the equilibrium objects at the aggregate level, but because we have omitted the time fixed effects for presentational purposes, it cannot be directly seen from this definition. In Appendix B.2 I connect all the concepts in this section with the macro elasticities.

regional level to get:

$$\overline{y}_n - \beta_{pe}\overline{z}_n = \gamma_P\phi_P\overline{z}_n + \gamma_W\phi_W \sum_{b\in B_n}\omega_{nb}\sum_{c\in C_b} l_{cb}\overline{z}_c + \gamma_P v_n^P + \gamma_W \sum_{b\in B_n}\omega_{nb}v_b^W + \overline{\varepsilon}_n,$$

and define:

$$h_{ge}\left(\{\overline{z}_c\}_{c=1}^N ; n\right) = \gamma_P\phi_P\overline{z}_n + \gamma_W\phi_W \sum_{b\in B_n}\omega_{nb}\sum_{c\in C_b} l_{cb}\overline{z}_c.$$

I will also denote as $\mathbf{1}$ the $N \times 1$ vector of ones, i.e. $\mathbf{1} = [1, ..., 1]'$. With these then we have the following definitions:

Definition 1. Given the function $h_{ge}\left(\{\overline{z}_c\}_{c=1}^N ; n\right)$:

1. The *local* regional multiplier, β_{LM}, is given by $\beta_{LM} = \partial h_{ge}(.)/\partial\overline{z}_n$;
2. The *global* regional multiplier, β_{GM}, is given by $\beta_{GM} = \nabla h_{ge}(.)'\,\mathbf{1} = \sum_{c=1}^N \partial h_{ge}(.)/\partial\overline{z}_c$.

It is straightforward to show, by direct computation, that the multipliers equal:[19]

$$\beta_{LM} = \gamma_P\phi_P + \gamma_W\phi_W\sum_{b\in B_n}\omega_{nb}l_{nb}, \quad \beta_{GM} = \gamma_P\phi_P + \gamma_W\phi_W.$$

Conceptually, both multipliers are defined by the same exercise of letting the regional equilibrium objects, house prices and lenders' net worth, adjust when we measure the impact on lending. For the local version we only let them adjust for the shocks in region n, while for the global version we let all the shocks impact house prices and net worth in region n. Which multiplier is of interest depends on the question being asked, and on the sources of variation available to measure them in practice, which may favor one over the other. I expand on these issues below when I discuss the decomposition from a public policy perspective, in Appendix B.3, and present the identification and estimation results, in Section 3.4.

3.3 The Housing Channel vs the Financial Intermediary Channel

The central task in this paper is to decompose the part of the regional multiplier that comes from the housing channel from the part that comes from the financial intermediary (FI) channel. At a conceptual level this can be done for either of the multipliers defined in the previous section.

[19] Because β_{GM} equals the product of the gradient with $\mathbf{1}$, it is the directional derivative of $h_{ge}(.)$ along the direction $\mathbf{1}$. Moreover, β_{LM} should be indexed by n, but to keep the notation simple I omit this dependence unless it becomes relevant.

Analogously to the definitions there, I take:

$$g_{hp}\left(\overline{z}_n; W_n\right) = \gamma_P \phi_P \overline{z}_n + \gamma_W W_n$$
$$g_{nw}\left(\left\{\overline{z}_c\right\}_{c=1}^N; P_n, n\right) = \gamma_P P_n + \gamma_W \phi_W \sum_{b\in B_n} \omega_{nb} \sum_{c\in C_b} l_{cb} \overline{z}_c,$$

and define:

Definition 2. Given the functions $g_{hp}\left(.\right)$ and $g_{nw}\left(.\right)$:

1. The *housing channel* of the *local* and *global* regional multipliers is given by $\partial g_{hp}\left(.\right)/\partial \overline{z}_n$;
2. The *financial intermediary channel* of the *local* regional multiplier is given by $\partial g_{nw}\left(.\right)/\partial \overline{z}_n$;
3. The *financial intermediary channel* of the *global* regional multiplier is given by $\nabla g_{nw}\left(.\right)' \mathbf{1} = \sum_{c=1}^N \partial g_{nw}\left(.\right)/\partial \overline{z}_c$.

By direct computation we have:

$$\partial g_{hp}\left(.\right)/\partial \overline{z}_n = \gamma_P \phi_P,\ \partial g_{nw}\left(.\right)/\partial \overline{z}_n = \gamma_W \phi_W \sum_{b\in B_n} \omega_{nb} l_{nb},\ \sum_{c=1}^N \partial g_{nw}\left(.\right)/\partial \overline{z}_c = \gamma_W \phi_W.$$

And note that the channels sum to the corresponding multiplier:

$$\beta_{LM} = \partial g_{hp}\left(.\right)/\partial \overline{z}_n + \partial g_{nw}\left(.\right)/\partial \overline{z}_n \tag{9}$$
$$\beta_{GM} = \partial g_{hp}\left(.\right)/\partial \overline{z}_n + \sum_{c=1}^N \partial g_{nw}\left(.\right)/\partial \overline{z}_c, \tag{10}$$

so I will sometimes also refer to, e.g., the share of the credit multiplier coming from the housing channel, $\frac{\partial g_{hp}(.)/\partial \overline{z}_n}{\beta_{GM}} = \gamma_P \phi_P/\beta_{GM}$.

What the decompositions in equations (9) and (10) capture is the part of the multiplier that comes because of the reaction of the net worth of the lenders in the region vis-à-vis the region's house prices. To build intuition, we can focus on equation (10). What this decomposition is saying is that when all the regions experience a small shock dz, in addition to the increase in lending coming from the partial equilibrium effect of $\beta_{pe} dz$, house prices in region n will increase by $\phi_P dz$, and because of this increase lending is going to increase by $\gamma_P \phi_P dz$. At the same time, the net worth of the lenders in the region will expand by $\phi_W dz$ and, because of this, lending will further increase by $\gamma_W \phi_W dz$. If we add up both effects we obtain the total amount of amplification, $\beta_{GM} dz$. For a more detailed discussion of what the decomposition is capturing, see Appendix B.3.

3.4 Identification and Estimation

Identification and estimation follows from standard 2SLS and OLS results once one has a strategy for estimating the decompositions. I will focus first on the global multiplier and then on the local one. After these results I discuss the main threats to identification, which are crucial to understand the robustness of the estimates.

The strategy to decompose β_{GM} is to actually determine each of its components separately. First, following Mian, Sarto and Sufi (2023) I obtain $\hat{\beta}_{pe}$ using a least square dummy variable estimator with region fixed effects applied to (5). Because the time fixed effects have already been differenced out, this is effectively using region-by-time fixed effects.[20] The first identification assumption is then:

Assumption 1. $\mathbb{E}\left[\left(z_{in} - \frac{1}{I}\sum_{i=1}^{I} z_{in}\right)\left(\varepsilon_{in} - \frac{1}{I}\sum_{i=1}^{I} \varepsilon_{in}\right)\right] = 0, \forall i, n.$

Given Assumption 1 we know $\hat{\beta}_{pe} \xrightarrow{p} \beta_{pe}$ as $N \to \infty$.

Second, we estimate via 2SLS:

$$\overline{y}_n - \hat{\beta}_{pe}\overline{z}_n = \gamma_P P_n + \gamma_W W_n + \overline{\varepsilon}_n, \tag{11}$$

instrumenting (P_n, W_n) with $(\overline{z}_n, \sum_b \omega_{nb} \sum_c l_{cb}\overline{z}_c)$, to obtain estimates $(\hat{\gamma}_P, \hat{\gamma}_W)$. In addition to the key exogeneity condition on the shocks, which I write down explicitly below, the crucial assumption in this step is that house prices in the region and the net worth of the lenders in it, or some measure of their lending capacity, depend on a different set of shocks to the other regions in the economy such that the rank condition for identification is satisfied.

More precisely, the equations for (P_n, W_n) in system (5)-(8) are given by:

$$P_n = \phi_P \overline{z}_n + v_n^P \tag{12}$$

$$W_n = \phi_W \sum_{b \in B_n} \omega_{nb} \sum_{c \in C_b} l_{cb}\overline{z}_c + \sum_{b \in B_n} \omega_{nb} v_b^W. \tag{13}$$

Equation (13) implicitly defines a network that connects each region n's outcome with the credit supply shocks of the other regions (its own included). Equation (12) is the same, with the difference that is more extreme and says only the shocks in its own region matter for house prices. In our application below I present evidence that this is indeed the case: house prices do not depend on shocks to far away regions, once one conditions on the local shocks. In contrast, I show that lenders' net worth does depend on shocks to far away regions. The intuition is that housing markets are geographically segmented, whereas in

[20] And as pointed out before, the system is already in first differences, so it allows panel fixed effects as well.

any given region there are lenders that operate in many other regions simultaneously. Thus, lenders in the region transmit, through their balance sheets, spillovers from regions that are very far away. This asymmetry drives the difference between the specifications of (12) and (13). However, even though our specification is driven by the specific objective of looking at the credit boom, I should point out that a sufficiently different network is all that is needed for the rank condition.

The key assumptions for $(\hat{\gamma}_P, \hat{\gamma}_W)$ are then:

Assumption 2. $\mathbb{E}\left[\left(\overline{z}_n, \sum_b \omega_{nb} \sum_c l_{cb}\overline{z}_c\right)' \varepsilon_n\right] = 0$ *and rank* $\mathbb{E}\left[\left(\overline{z}_n, \sum_b \omega_{nb} \sum_c l_{cb}\overline{z}_c\right)' (P_n, W_n)\right] = 2, \forall n.$

Under Assumption 2 we know $(\hat{\gamma}_P, \hat{\gamma}_W) \xrightarrow{p} (\gamma_P, \gamma_W)$ as $N \to \infty$.

The final step is simply to estimate (12) and (13) via OLS to get $\left(\hat{\phi}_P, \hat{\phi}_W\right)$. For this we need:

Assumption 3. $\mathbb{E}\left[\overline{z}_n v_n^P\right] = 0$ *and* $\mathbb{E}\left[\left(\sum_b \omega_{nb} \sum_c l_{cb}\overline{z}_c\right)\left(\sum_b \omega_{nb} v_b^W\right)\right] = 0, \forall n.$

With Assumption 3 we know $\left(\hat{\phi}_P, \hat{\phi}_W\right) \xrightarrow{p} (\phi_P, \phi_W)$ as $N \to \infty$.

At this point we have all the elements we need to construct and estimate of the global multiplier:

$$\hat{\beta}_{GM} = \hat{\gamma}_P \hat{\phi}_P + \hat{\gamma}_W \hat{\phi}_W, \tag{14}$$

as well as both channels. The housing channel is given by $\hat{\gamma}_P \hat{\phi}_P$ and the FI channel by $\hat{\gamma}_W \hat{\phi}_W$. Under Assumptions 1, 2, and 3, all the estimators in $\hat{\beta}_{GM}$ are consistent, so $\hat{\beta}_{GM} \xrightarrow{p} \beta_{GM}$ as $N \to \infty$, and the same holds for the channels. To estimate the local multiplier I follow the same procedure, but I multiply the FI channel by $\sum_{b \in B_n} \omega_{nb} l_{nb}$; the housing channel is identical.

3.4.1 Threats to Validity

At a conceptual level there are two kinds of threats to the identification and consistency results in the previous paragraphs. One is related to the shocks themselves and it is a standard concern on any instrument, which is, for example in our case, whether one has a measure of a credit supply shock that is contaminated by demand components or not. The other kind is related to the structure of the system (5)-(8). For example, as I mentioned before, equation (13) implicitly defines a network that connects each region n's outcomes with the credit supply shocks of the other regions. What happens if we misspecify the network? Similarly, equation (11) says there are two channels that transmit the regional spillovers. How do we know we are not missing additional channels? In this section I address these types of concerns.

Network Misspecification The first concern I tackle is network misspecification. Because equation (13) has the richer set of interactions, I develop the main points using that equation, but the same issues apply to equation (12). Moreover, although I focus on equations (12) and (13), I should note that misspecifying the network also creates problems for the 2SLS estimators ($\hat{\gamma}_P$, $\hat{\gamma}_W$). From the perspective of the 2SLS step, equations (12) and (13) are the relevant reduced forms. Thus, the less we capture the true interactions among regions, the less variation we capture in those reduced forms, leading to a weak instruments problem. However, the weak instruments problem is well understood conceptually, so I leave it aside.

The main analytic result in Proposition 2 below says that, as long as we capture the network correctly in term of its linkages, the estimators are consistent. That is, the network that connects region n's outcomes with the credit supply shocks of the other regions can we wrong because we connect region n with a wrong set of regions, or because the set is correct but the weight assigned to each link is incorrect, or both simultaneously. Proposition 2 says whether we are using the correct set of weights to connect the different regions is not relevant asymptotically, as long as we are connecting the right set of regions with each other.[21] This, in turn, implies that if we misspecify the set of regions then we will start injecting bias in our estimates. In order to study this in more detail, after presenting the analytic result I provide simulations that show the effect of misspecifying the set of regions by 20%, in the sense that, for each region n, one fifth of the set of regions it gets connected to is incorrect. The takeaway from that exercise is that the effects on the multipliers are significant, but the effects on the shares explained by each channel are very small.

To present the analytic result, let us rewrite the regressor in (13) as $\sum_c \overline{z}_c \left(\sum_b \omega_{nb} l_{cb}\right)$, where $l_{cb} = 0$ if $c \notin C_b$, $\omega_{nb} = 0$ if $b \notin B_n$. Thus, suppose that instead of using the correct weights, $\sum_b \omega_{nb} l_{cb}$ for each $\overline{z}_c$, we use the incorrect weights $\widetilde{w}_{nc}$. The OLS estimator $\widetilde{\phi}_W$ in this case would be given by:

$$\begin{aligned}\widetilde{\phi}_W = \phi_1^{NW} &+ \frac{\sum_n \left(\sum_{c\in\mathcal{N}(n)} \widetilde{w}_{nc}\overline{z}_c\right)\left(\sum_b \omega_{nb}\varepsilon_b^{NW}\right)}{\sum_n \left(\sum_{c\in\mathcal{N}(n)} \widetilde{w}_{nc}\overline{z}_c\right)^2} \\ &- \phi_1^{NW} \frac{\sum_n \left(\sum_{c\in\mathcal{N}(n)} \widetilde{w}_{nc}\overline{z}_c\right)\sum_{c\in\mathcal{N}(n)} \left\{\widetilde{w}_{nc} - \left(\sum_b \omega_{nb} l_{cb}\right)\right\}\overline{z}_c}{\sum_n \left(\sum_{c\in\mathcal{N}(n)} \widetilde{w}_{nc}\overline{z}_c\right)^2},\end{aligned} \tag{15}$$

[21] Cases in which one region, or a small set of regions, become "dominant" as $N \to \infty$, in the sense that, e.g., their combined weight in the network tends to 100%, are ruled out by the conditions in the proposition.

where $\mathcal{N}(n)$ denotes the set of regions that belong to the network of region n. That is, $c \in \mathcal{N}(n)$ if $\sum_b \omega_{nb} l_{cb} > 0$. If we change $\widetilde{w}_{nc}$ for $\sum_b \omega_{nb} l_{cb}$ in the second term on the RHS of (15), the first two terms are exactly the same as the ones we would get if we used the correct weights. Because of Assumption 3 the second term vanishes as $N \to \infty$ whether we use the correct weights or not. Hence, the interesting question is what happens to the third term on the RHS of (15). The following result says that as long as we capture the network correctly in terms of whether regions are connected or not, this term vanishes as well:

Proposition 2. *Suppose* $card\left[\mathcal{N}(n)\right] = M\ (\forall n)$, $\overline{z}_c = \alpha z_{\mathcal{N}(c)} + \varepsilon_c^z$, *the weights satisfy*:

1. $\mathbb{E}\left[\widetilde{w}_{nc}^2\right] = O\left(M^{-2}\right)$, $\mathbb{E}\left[\left(\sum_b \omega_{nb} l_{cb}\right)^2\right] = O\left(M^{-2}\right)$,

and the shocks ε_c^z *satisfy*:

2. $\mathbb{E}\left[\varepsilon_c^z \middle| \widetilde{w}_{nc}^2\right] = \mathbb{E}\left[\varepsilon_c^z \middle| \left(\sum_b \omega_{nb} l_{cb}\right)^2\right] = 0$,
3. $\mathbb{E}\left[\left(\varepsilon_c^z\right)^2 \middle| \widetilde{w}_{nc}^2\right] = \mathbb{E}\left[\left(\varepsilon_c^z\right)^2 \middle| \left(\sum_b \omega_{nb} l_{cb}\right)^2\right] = \sigma_{\varepsilon^z}^2$,
4. $\mathbb{E}\left[\varepsilon_c^z \varepsilon_j^z \middle| \widetilde{w}_{nc}, \widetilde{w}_{nj}\right] = \mathbb{E}\left[\varepsilon_c^z \varepsilon_j^z \middle| \sum_b \omega_{nb} l_{cb}, \sum_b \omega_{nb} l_{jb}\right] = 0$ *for* $c \neq j$,

then:

$$\frac{1}{N}\sum_n \left(\sum_{c\in\mathcal{N}(n)} \widetilde{w}_{nc}\overline{z}_c\right)\left(\sum_{c\in\mathcal{N}(n)} \left\{\widetilde{w}_{nc} - \sum_b \omega_{nb} l_{cb}\right\} \overline{z}_c\right) = o_p(1).$$

Proposition 2 shows that as long as the set of regions to which each region gets connected is correct, the weights assigned to each link are irrelevant. To evaluate the effects of misspecifying the set of regions I present simulations, in Table 14 of Appendix B, in which 20% of the set of regions each region gets connected to is incorrect. As we can see from the table, the effects on the absolute values can be large, but the effect on the shares explained by each channel is very small. Section B.4.1 offers a very detailed discussion of this exercise, plus additional ones for other cases.

Taken together, these two results are very reassuring for our empirical application in Section 4 below. The reason is that we can be less worried about the exact specifications for the weights ω_{nb}s and l_{cb}s. In our empirical results, I present estimates using networks defined by the geographic patterns of both mortgage loans and deposits raised by banks across the U.S. Based on the results in this section, the key aspect we want from these networks is that they connect the correct set of regions with each other, but we are not worried about the specific weight attached to each link. Thus, even though it is difficult to guarantee we have assigned the correct weight to each link, it seems implausible that the correct specification would be too far away from one that connects regions based on the lending and deposit taking activities. And as the simulations of Table 14 show, even decently sized mistakes in the latter can have small effects in the decomposition. Moreover, I also present empirical tests that lend support to our preferred specification in terms of the network. Hence, although it is very difficult to completely rule out a role for network misspecification, the results in this section, coupled with the empirical tests, provide very strong support to the empirical results.

These results also highlight that in applications in which one is less certain about the network links (regardless of the weight assigned to each link), the local regional multiplier, and its decomposition, are much more robust. This is because in most applications, if not all, every region is going to have its own shock appear in its network. Depending on how many links are missing from the connections to other regions, the global multiplier will be biased (e.g. downwards when there are strategic complementarities across regions). In the case that shocks to the different regions are uncorrelated within the network, the local multiplier and its decomposition will remain unbiased.

Confounding the Credit Supply Shock Another concern for identification is that the credit supply shock we are relying on is not "pure". In particular, the worry is that it might be contaminated by a demand shock. Of course, as with any identification strategy that tries to isolate a shock, it is impossible to completely rule out this possibility. However, there are many reassuring elements that makes this a small concern for our task of decomposing the multiplier. The first one is that both in the theory in this section, and in the empirical application of Section 4 below, the point of departure is a credit supply shock that is extremely granular. It is a shock that varies across lenders within the same county. In fact, our estimates of the partial equilibrium effect actually relies on county-by-time fixed effects. So the confounding piece should vary by lenders within the same county in a way that lines up with the supply shock, which seems highly implausible.

This is an important aspect because of the following point. The parts that would be affected from the procedure that leads to $\hat{\beta}_{GM}$ in (14) depend on whether the confounder has a partial equilibrium effect, a general equilibrium effect, or both. Table 1 summarizes the consequences of each case for the estimates. The upper left quadrant in Table 1 reflects the case of no confounding shock. The meaning of "P_n, W_n valid" is that $\left(\hat{\phi}_P, \hat{\phi}_W\right)$ are consistent, and "2SLS valid" means $(\hat{\gamma}_P, \hat{\gamma}_W)$ are consistent. Thus, for example in the first column where the confounding shock does not have a partial equilibrium effect, the 2SLS estimates remain valid regardless of whether it has a general equilibrium effect or not. The reason is that for the 2SLS estimates we only need the reduced forms of P_n and W_n, so whether they have a mixture of both shocks is irrelevant. This is important because one of the main contributions of this paper is to estimate the effects of house prices and lender's lending capacity during the credit boom. As highlighted before, the granularity of the credit supply shocks used in our empirical application means that it is highly likely we find ourselves in the left column of Table 1, and thus this part of the contribution would be completely unaffected by it.

Demand shock	$PE = 0$	$PE \neq 0$
$GE = 0$	P_n, W_n valid 2SLS valid	P_n, W_n valid 2SLS invalid
$GE \neq 0$	P_n, W_n invalid 2SLS valid	P_n, W_n invalid 2SLS invalid

Table 1: Components of $\hat{\beta}_{GM}$ affected depending on the nature of the confounding shock.

However, even in the case that the confounding shock has a general equilibrium effect, there is an unexpected benefit of looking at the channel decomposition we are interested in. The benefit comes from the fact that any confounding shock during the credit boom would most likely have induced an upward bias in our estimates $\left(\hat{\phi}_P, \hat{\phi}_W\right)$. But because the share of the channels is a ratio, such as $\gamma_P \phi_P / (\gamma_P \phi_P + \gamma_W \phi_W)$ for the housing channel, the confounder needs to be highly asymmetric between P_n and W_n for the share to change meaningfully. To study this in more detail I perform simulations in Table 15 of Appendix B, and we see that, although the multiplier can be severely biased upwards by the confounder, the share explained by each channel is only mildly affected. The reason is precisely that the confounder biases upwards both channels with a similar strength, and thus the ratio does not change much. See Section B.4.1 for a detailed discussion of this exercise.

Channels The third concern one might have in our framework is whether there are missing channels from equation (11). That is, in addition to the region's house prices and lenders' lending capacity, are there other channels contributing to the rise in credit? The answer to this question is that, if one has access to more than two instruments, the Sargan-Hansen test can be used to test the over-identifying restrictions. Although, as in every instance of this test, there are additional dimensions related to e.g. modeling assumptions being tested jointly, failure to reject the test is evidence that we have captured all the relevant channels. In the empirical results in the next section I present various instances of this test and many specifications that fail to reject. This is remarkable if one considers that a model that is 99% correct will reject the null with enough data, and in the lender-county level specifications we have around $50,000$ observations in the setup of Mian and Sufi (2021) and around $25,000$ in the setup of Di Maggio and Kermani (2017).

4 Dissecting the Rise in Credit: Exploiting the PLS Surge and APL laws

In this section I apply the results in previous section to the setup in Mian, Sarto and Sufi (2023) using the credit supply shocks of Mian and Sufi (2021) and Di Maggio and Kermani (2017). I first detail the data sources and I then present the main results. The next section presents an extensive set of robustness tests, along with explorations of heterogeneity and a closer look at local multipliers.

4.1 Data Sources

Mortgage lending Mortgage lending data comes from HMDA. The HMDA data set records the universe of mortgage originations for mortgage originators that have an office within metropolitan statistical areas (MSAs). I also link the data in HMDA to the Call Report data. For loan amounts I use the sum of loans originated for purchasing a house and for refinancing previous loans.

Bank income and balance sheets The bank-level data are from the Consolidated Reports of Condition and Income, better known as Call Reports, hosted by the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution. This data contains quarterly information on income statements and balance sheets for every national bank, state member bank, insured state non-member bank, and savings association in the U.S.

Branch-level deposits The branch-level deposits data comes from the FDIC's Summary of Deposits. This data contains annual information on the amount of deposits for all FDIC-insured institutions.

House prices The data on house prices comes from the monthly Home Price Index (HPI) of CoreLogic, which is recorded at the zip code level.

Demographics I use county-level census-based data on demographics, income and business statistics.

County-MSA Crosswalk For the mapping between the county level data and the metropolitan statistical areas (MSAs) I use the QCEW County-MSA-CSA Crosswalk, provided by the U.S. Bureau of Labor Statistics, and apply the post-2003 definition of MSA borders.

4.2 Research Design, Overview of the Variables and OLS

In this section I present the main variables that I will use in the decomposition in the next section, and I also present the results from estimating equation (11) via OLS, which will serve as a benchmark for our 2SLS estimates. To construct the net worth growth rate in (11) I use equation (7) using bank b's share of total deposits in county n as ω_{nb}. Later in our empirical investigation, I also use the share of mortgage loans in county n for the ω_{nb}s. For W_b I use the equity growth rate of bank b. In principle, based on the ideas of Section 2, one would like some measure of the lending capacity of the lenders in the county during this period. Even though in a model one can be less specific, it is not entirely clear what would be the perfect counterpart in the data. For sure the capital of banks operating in the county is a first order dimension to take into account, but it is impossible to rule out that a different, related, measure fits our purpose better. In the same fashion, it would be nice to add the capital of shadow banks to our measure of W_n. However, the average shadow bank share during this episode is only slightly higher than 25% in 2000,[22] so it is probably less of a concern.

Figure 1 shows the result of projecting the lending growth rate over the house price growth rate, in panel a, and net worth growth rate, in panel b, during the period 2000-2005, at the county level. As we can see from both panels, there is a very strong positive relationship. That is, there is a very strong comovement between lending and house prices and between lending and net worth. Based on the housing boom and expansion in credit supply, which played a central role during the credit boom, both panels of Figure 1 are to be expected.

PLS surge The first credit supply shock I exploit comes from Mian and Sufi (2021) and is based on the rise of the private label securitization market that surged in the early 2000s. Justiniano et al. (2022) show that events around the summer of 2003 triggered this surge, and Mian and Sufi (2021) exploit the fact that this surge enabled lenders relying on non-core deposit financing to increase mortgage supply more aggressively. This expansion meant that counties which housed lenders that relied relatively more on non-core deposit financing ("high NCL lenders") saw a rapid and aggressive increase in their mortgage originations.

Thus, in terms of the notation in Section 3.4, I take z_{in} to be the NCL ratio of lender i in county n, and construct $\overline{z}_n$ as the weighted average of the NCL ratios of the banks in the county, using their participation on total originations within the county as the weights. The

[22] See, for example, Sarto and Wang (2023).

main instruments I construct for the 2SLS step, and to estimate equations (12) and (13), are:

$$\text{Regional NCL}_n = 0.25 \times \overline{z}_n + 0.75 \times State\_NCL(n) \tag{16}$$

$$\text{Deposit Network NCL}_n = \sum_{b \in B_n} \omega_{nb} \sum_{c \in C_b} l_{cb} \overline{z}_c, \tag{17}$$

where $State\_NCL(n)$ is the population weighted average of the $\overline{z}_n$s in county's n state (excluding county n), and I use the deposit network for the ω_{nb}s and l_{cb}s in (17). That is, ω_{nb} is bank b's share of total deposits in county n, and similarly for l_{cb}. In Section 5 I show robustness tests where I use the mortgage loan network instead, and I also show tests in which I change the 0.25/0.75 weighting scheme in (16).

The instrument in (16) is tailored to the housing market.[23] The idea behind it is that, once we measure the impact of the credit supply shocks that are within the county and in nearby counties, shocks to very far away regions are not relevant at the regional level because housing markets are geographically segmented. In contrast, the idea behind equation (17) is that for counties with lenders that operate nationally, or in many regions simultaneously, shocks to regions that are far away can have a large impact, and hence become relevant for the local environment. Figure 5 in Appendix B shows the weights attached to each county in both instruments for New York county. As we can see from panel a, in the regional NCL counties close to New York county tend to receive larger weights than those further away but within New York state. All counties outside of New York state receive zero weight. In contrast, in panel b we see that the deposit network NCL assigns positive weights to counties that are very far away, even counties in the west coast. The reason for this is that if there are lenders that raise deposits (or grant loans in our alternative measure that relies on the mortgage lending network instead) in New York county that also raise deposits in, e.g., San Francisco county, then equation (17) assigns positive weight to San Francisco county.

States' APL laws The second credit supply shock I exploit comes from Di Maggio and Kermani (2017), and is based on the 2004 preemption rule enacted by the Office of the Comptroller of the Currency (OCC) that banned the application of antipredatory-lending laws to national banks and its mortgage lending subsidiaries. Using a triple-difference strategy based on national banks operating in states which had APLs by 2004, the authors

[23] A short note on language. Because of the 2SLS step, all the credit supply shocks and their functions serve as instruments. However, to decompose the multipliers and estimate the different channels their causal impact on house prices and lenders' net worth are also of interest. The distinction is relevant because the latter is not needed from an arbitrary instrument in an IV setup. Nonetheless, I will keep the language loose in this sense to facilitate the presentation, unless the distinction becomes relevant.

show that this resulted in an expansion of credit supply by national banks.

Hence, in terms of the notation of Section 3.4, in this case I take z_{int} to be $APL_{g,t} \times Post_{2004} \times OCC$, where $APL_{g,t}$ is an indicator variable equal to one if state g has an antipredatory-lending law, $Post_{2004}$ equals 1 after the enactment of the preemption rule, and OCC equals 1 if the originator is regulated by the OCC. With the same logic as (16)-(17) I take:

$$\text{Regional APO}_{nt} = \overline{z}_{nt} \tag{18}$$

$$\text{Deposit Network APO}_{nt} = \sum_{b \in B_n} \omega_{nb} \sum_{c \in C_b} l_{cb} \overline{z}_{ct}, \tag{19}$$

where, following Di Maggio and Kermani (2017) and Mian, Sarto and Sufi (2023), $\overline{z}_{nt} = APL_{g,t} \times Post_{2004} \times OCC_{2003}$ and OCC_{2003} is the fraction of purchase loans originated by OCC lenders in 2003 in county n. The weights ω_{nb} and $l_{cb}$are exactly as in (17), with the only difference that in (17) I use 2002 for them because the PLS surge application runs from 2002 to 2005, whereas (19) uses 2000 weights, because this application runs from 2000 to 2006. Moreover, because there is such a strong state level component already in $\overline{z}_{nt}$, I only include counties for which $APL_{g,t} = 1$ in (17), and, for the same reason, in (18) I rely only on county n; as I show below, the exact same ideas behind the discussion of (16)-(17) apply in this case. Figure 4 mimics Figure 5, and shows the weights used in (19), also for New York county.

4.3 The Housing Channel vs the Financial Intermediary Channel

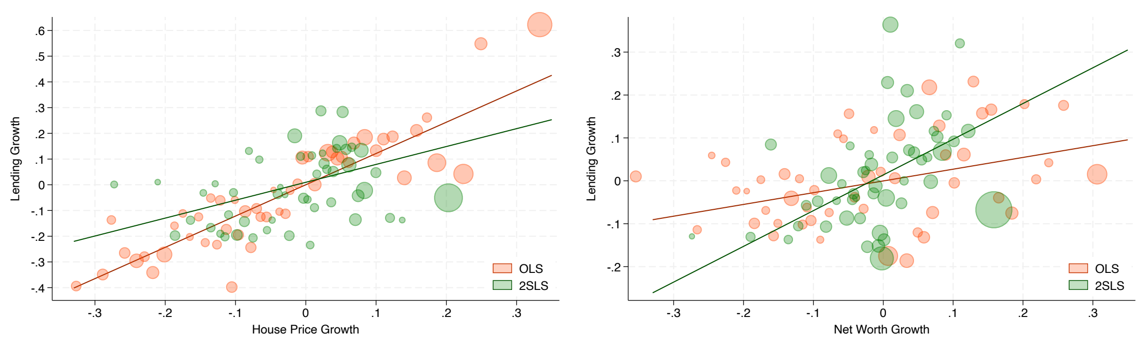
In this section, I present the main 2SLS results from estimating equation (11). This is one of the principal contributions of the study, since these results document how the rise in credit above the partial equilibrium effects that we observed depended on the housing market and lenders' unlocked lending capacity. After this, I look at the effects of the shocks on house prices and lenders' net worth, and I construct the global multiplier and its decomposition; this is the second main contribution of this paper.

4.3.1 2SLS results

PLS surge I begin by presenting the 2SLS results that exploit the PLS surge that started in 2003. Figure 2 shows the main 2SLS specification against the OLS estimates of equation (11). To facilitate capturing the patterns, the charts are constructed as binned scatter plots, and in each panel the other endogenous regressor has been partialed out. As we can see, the OLS estimates tend to overestimate the role of house prices, and tend to underestimate the role of lenders' net worth. There is still a very strong positive relationship from both variables in the 2SLS specifications, but there is a noticeable difference when compared to the OLS estimates.

This pattern is consistent with a data generating process in which lending affects both house prices and lenders' net worth, but with a stronger effect in the former. Many of the smaller lenders, which have a higher tendency to operate locally, certainly have a large exposure to the housing market, but there are many large lenders for which mortgage lending is a fraction of their operations. Thus, it is indeed plausible that lending has a stronger effect on house prices than on net worth at the regional level. By removing this source of bias, under 2SLS, the effect of net worth increases and the effect of house prices decreases.

Table 2 shows the regressions behind Figure 2, along with additional specifications. Column 1 shows the partial equilibrium effect, estimated at the lender level following Mian, Sarto and Sufi (2023). This is the estimate I use to construct the dependent variable in equation (11). Column 2 shows the OLS results which correspond to the orange circles in Figure 2. As we can see, there is a very strong positive relationship from both house prices and net worth, but the effect seems to be much larger for the former. The conditional elasticity of net worth is around 0.3, meaning that a 10% increase in lenders' net worth is associated with a 3% increase in lending (above the partial equilibrium effect) controlling for house prices. For house prices, a 10% increase is associated with a 12% increase in lending, controlling for net worth.



(a) House Prices

(b) Net Worth

Figure 2: Lending against house prices (panel a) and net worth (panel b).
The figure shows binned scatter plots of lending growth against house price growth (panel a) and against net worth growth (panel b) during the 2002-2005 period at the county level. For both panels, the partial equilibrium effect of the credit supply shocks has been netted out, as in the left hand side of equation (11). In panel a, net worth has been partialed out; in panel b, house price growth has been partialed out. The solid lines correspond to OLS and 2SLS regressions with county population in 2002 as weights. Circle size indicates the bin's population as of 2002.

Column 3 shows the 2SLS results depicted in Figure 2. In addition to the regional NCL and deposit network NCL measures from equations (16) and (17), I also include the housing supply elasticity of Saiz (2010). Several studies (Mian and Sufi, 2009, 2011; Mian et al., 2013)

Table 2: Lending Growth, 2002-2005

	OLS		2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
NCL 2002	0.631**					
	(0.306)					
Net Worth Growth		0.274***	1.009***	0.991***	0.828***	0.902***
		(0.105)	(0.199)	(0.201)	(0.177)	(0.188)
House Price Growth		1.216***	0.643***	0.597***	0.664***	0.627***
		(0.158)	(0.198)	(0.201)	(0.202)	(0.202)
	Instruments/Controls					
County FE	YES					
Regional NCL			YES	YES	YES	YES
Deposit network NCL			YES	YES	YES	YES
Elasticity			YES	YES	YES	YES
Regional NCL × Elast.				YES	YES	YES
Regional elast. (dep)					YES	
Regional elast. (loa)						YES
Level	Lender	County	County	County	County	County
Kleinbergen-Papp F	-	-	30.80	23.36	20.72	19.42
Hansen J (p-value)	-	-	0.63	0.19	0.02	0.03
N	90457	615	497	497	497	497
R-sq	0.160	0.536	0.465	0.459	0.490	0.476

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table reports estimates of least square regressions, weighted by the county's population in 2002 (cols (2)-(6)) and the lending share in the county interacted with the county's 2002 population (col (1)). Column (1) relates the lender's loans growth to their NCL as of 2002. Columns (2)-(6) relate the county's loans growth, net of the PE effect estimate of column (1), to the county's net worth growth and house price growth. Column (1) includes county fixed effects. Columns (3)-(6) use the regional and deposit network NCLs, as well as the housing supply elasticity, as instruments. Column (4) adds the regional NCL interacted with the housing supply elasticity, column (5) further adds the deposit network elasticity, and column (6) instead adds the mortgage loan network elasticity. The period considered is 2002-2005. Net worth growth was trimmed at the 5% level. Robust standard errors, clustered at the county and bank holding company levels in column (1), are below the coefficients in parentheses.

have shown the housing supply elasticity is a very useful instrument for the housing boom-bust cycle: it is orthogonal to a set of important variables that one might view as endogenous and interrelated to the housing cycle, and is a powerful predictor of house price growth during the credit boom. Comparing column 3 with column 2 we see that there is a large statistical and economic difference between the 2SLS estimates and their OLS counterparts. The conditional elasticity of net worth is now 1, meaning a 10% increase in lender's net worth generates a 10% increase in lending, above the partial equilibrium effect of the credit supply shock and holding house prices fixed. This compares to a 3% increase under OLS. The effect of house prices, in turn, decreases to 0.65, meaning a 10% increase in house prices generates a 6.5% increase in lending, above the partial equilibrium effect and holding the counties net worth fixed. Thus, the effects of house prices and net worth are much more balanced and in line with each other under the 2SLS specification. This points to both having played a similar role in amplifying the cycle, conditional on receiving the same impulse.

As we can see from column 3, the Kleinbergen-Papp F is 30.80, well above the usual thresholds for weak instruments. Moreover, it is remarkable that the Sargan-Hansen J p-value is 0.63: we fail to reject the null for the over-identifying restrictions tests at any conventional level of significance. This is strong evidence that there are not meaningful channels missing during the PLS surge. Even more, considering how easy it is for this test to fail given enough data, this bolsters the confidence in the estimates significantly. Below I also show this is true under another estimation strategy that relies on the lender level dataset, which brings the number of observations to around $50,000$. All these considerations are also consistent with the R^2 close to 50%.

In columns 4-6 I include additional specifications that progressively add instruments to the 2SLS specification in column 3. Column 4 adds the interaction of the housing supply elasticity with the regional NCL. Columns 5 and 6 add the deposit and mortgage loans networks of the housing supply elasticity, respectively. The latter are obtained as in equation (17), using the housing supply elasticity instead of $\overline{z}_c$. In column 5 I use the deposit network to do this and in column 6 I use the mortgage loans network. Overall, the estimates in columns 4 through 6 remain very stable and in line with those in column 3. Furthermore, the robust first stage F is also comfortably above the usual thresholds for weak identification. As we add the additional instruments though, the Sargan-Hansen J p-value starts to decrease, particularly in columns 5 and 6, but this is reasonable given we are adding a significant amount of restrictions in those columns. The R^2s remain also around 50%.

In Table 8 in Appendix B, I change the estimation strategy and switch to equation (5). I estimate that equation via 2SLS using the same type of instruments, but now at the lender level. There are advantages and disadvantages of this approach in comparison to the strategy in Table 2. The first order advantage is that it allows us to estimate the partial equilibrium effect jointly with the effects of house prices and net worth. The disadvantage is that the partial equilibrium estimate from Table 2 is more robust, given its reliance on the county fixed effects, and thus the amplification that is being decomposed is estimated more accurately. As we can see from the first row in any of the 2SLS columns though, the estimates of the partial equilibrium effects are essentially the same as those estimated in Table 2, which is very reassuring.

Table 8 presents regressions weighted by lending shares interacted with the county's population in 2002. Columns 1 through 3 have standard errors that are clustered at the bank holding company level, and columns 4 through 6 have standard errors that are clustered at the county and bank holding company level. Because I weight by population, our preferred specifications are the ones that cluster by bank holding company only, because the number of clusters in this dimension is very high, above $3,000$, whereas the number of counties is similar to that in Table 2. I show both set of results nonetheless.

The second and third rows in Table 8 show the exact same patterns of Table 2. The OLS estimates severely underestimate the net worth effect, and simultaneously overestimate the effect of house prices. For example, the conditional elasticity of net worth in column 5 is

0.94, compared to 1 in column 3 of Table 2, and the conditional elasticity of house prices is 0.54, compared to 0.65 in Table 2. Moreover, the Kleinbergen-Papp F is well above the usual thresholds for weak instruments in all specifications. Finally, in line with the results on Table 2, the Sargan-Hansen J p-values are 0.47 and 0.57 in columns 2 and 5, which is remarkable given there are around 45,000 observations in those specifications. Thus, this again reinforces the notion that we are not missing additional channels during this episode.

Table 3: Lending Growth, 2002-2005

	Lender Level				County Level		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Net Worth Growth	0.872***	0.853***	0.872**	0.853**	0.516*	0.650**	0.486*
	(0.282)	(0.268)	(0.357)	(0.341)	(0.278)	(0.325)	(0.280)
House Price Growth	0.535***	0.539***	0.535**	0.539**	0.816***	0.622***	0.815***
	(0.195)	(0.195)	(0.268)	(0.267)	(0.234)	(0.232)	(0.232)
NCL 2002	0.603*	0.604*	0.603*	0.604*			
	(0.323)	(0.322)	(0.320)	(0.320)			
	Instruments						
Elasticity (county)	YES	YES	YES	YES	YES		YES
Regional elast. (loa)	YES	YES	YES	YES	YES	YES	YES
Elasticity (MSA)		YES		YES		YES	YES
Cluster	BHC	BHC	C & BHC	C & BHC	-	-	-
Hansen J (p-value)	-	0.43	-	0.66	-	-	0.15
Kleinbergen-Papp F	396.82	273.46	13.93	9.43	14.39	13.38	9.63
N	46818	46774	46818	46774	498	519	497
R-sq	0.079	0.080	0.079	0.080	0.532	0.458	0.531

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of 2SLS regressions, weighted by the lending share in the county interacted with the county's 2002 population (cols (1)-(4)) and by the county's population in 2002 (cols (5)-(7)). Columns (1)-(4) relate the lender's loans growth to their NCL as of 2002, and the county's net worth growth and house price growth. Columns (5)-(7) relate the county's loans growth, net of the PE effect estimate of Table 2 column (1), to the county's net worth growth and house price growth. All specifications include the regional elasticity (loans) as instrument. Columns (2), (4) and (6) further add the housing supply elasticity of the MSA to which the county belongs, and columns (1) through (5) and (7) include the county's housing supply elasticity. The period considered is 2002-2005. Net worth growth was trimmed at the 5% level. Robust standard errors, clustered at the bank holding company level in columns (1) and (2) and at the county and bank holding company levels in columns (3) and (4), are below the coefficients in parentheses.

Housing supply elasticities In Table 3 I show specifications that rely only on the housing supply elasticity instruments. This is an important test because any concern one might have on the credit supply shocks for the 2SLS step of the decomposition is completely irrelevant in these specifications. Moreover, as we can see from the Kleinbergen-Papp F row, the robust first stage Fs are all above 10, with the exception of two specifications for which it measures at 9.43 and 9.64. Thus, weak instruments is also not a concern in these specifications. The estimates are very much in line with the ones in Tables 2 and 8. The only noticeable difference are columns 4 and 7, in which the effects are slightly lower for net worth, and slightly higher for house prices. Hence, Table 3 confirms the general pattern from the previous results: compared to 2SLS, OLS severely under estimates the effect of net worth and overestimates the effect of house prices.

States' APL laws I now turn to the 2SLS results that exploit states' APL laws. In Table 4, columns 1 through 3, I use the same strategy of Table 8, estimating the partial equilibrium effect jointly with the effects of house prices and net worth. Following Di Maggio and Kermani (2017), the dependent variable in these columns is the log amount of home purchase mortgages originated by lenders regulated by different agencies. Columns 4 through 6 mimic the approach of Table 2, based on equation (11), with the dependent variable being the log of loan amounts in the county (net of the partial equilibrium effect). To construct the dependent variable of equation (11) in columns 4-6, I follow Mian, Sarto and Sufi (2023) and use the partial equilibrium estimates of Table 13, column 1, in Appendix B.

Table 4: Log of Loan Amount, 2000-2006

	Lender Level			County Level		
	OLS	2SLS		OLS	2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(\text{Net Worth})_{n,t}$	0.040***	0.301***	0.309***	0.035***	0.228***	0.236***
	(0.010)	(0.092)	(0.095)	(0.010)	(0.072)	(0.076)
$\log(\text{House Price})_{n,t}$	0.744***	1.026***	1.054***	0.847***	1.285***	1.311***
	(0.057)	(0.226)	(0.203)	(0.061)	(0.215)	(0.179)
$APL_{g,t} \times Post_{2004} \times OCC$	0.085**	0.112***	0.112***			
	(0.034)	(0.035)	(0.035)			
	Controls					
County-Agency FE	YES	YES	YES			
County FE				YES	YES	YES
Year FE & APO Controls	YES	YES	YES	YES	YES	YES
	Instruments					
Regional $\text{APO}_{n,t}$			YES			YES
Dep. Network $\text{APO}_{n,t}$		YES	YES		YES	YES
$\text{Post}_{2004} \times \text{OCC}_{2003}$		YES	YES		YES	YES
$\text{APL}_{g,t} \times \text{OCC}_{2003}$		YES	YES		YES	YES
Kleinbergen-Papp F	-	9.51	7.57	-	9.47	7.54
Hansen J (p-value)	-	0.22	0.25	-	0.47	0.37
N	28020	24149	24149	4672	4026	4026
R-sq	0.977	-0.001	-0.007	0.992	0.118	0.100

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of least squares regressions, weighted by the county's population in 2000, relating the (log) amount of newly originated loans under each regulatory agency to the county's (log) net worth, (log) house price level, and $APL_{g,t} \times Post_{2004} \times OCC$ (cols (1)-(3)), and the (log) amount of newly originated loans, net of the PE estimate $0.090 * APL_{g,t} \times Post_{2004} \times OCC_{2003} - 0.075 * Post_{2004} \times OCC_{2003} - 0.010 * APL_{g,t} \times OCC_{2003}$, to the county's (log) net worth and (log) house price level (cols (4)-(6)). All columns include year FE. Columns (1)-(3) include county-agency FE, and control for $APL_{g,t}, APL_{g,t} \times OCC, APL_{g,t} \times Post_{2004}, OCC \times Post_{2004}$. Columns (4)-(6) include county FE and control for $APL_{g,t}, APL_{g,t} \times Post_{2004}$. The sample includes years from 2000 to 2006. The (log) house price level was trimmed at the 1% level, and the deposit network APO at the 5% level. Robust standard errors, clustered at the county level, are below the coefficients in parentheses.

All columns in Table 4 are panel specifications over the period 2000-2006, so I include county-agency and year fixed effects in columns 1 through 3, and county and year fixed effects in columns 4 through 6. I should note though that, in the case of Table 4, the robustness advantage of using equation (11) in columns 4-6 is smaller than in the case of the PLS surge, because the strategy that relies on the APL laws requires controls that cannot be included when using county-year fixed effects.

As we can see from comparing columns 1 and 2, or columns 4 and 5, OLS severely underestimates the effect of net worth, as in previous results. Interestingly, the effect of house prices is also underestimated in this case. Thus, both coefficients increase when we move from OLS to 2SLS. And the differences are economically significant as well. For example, in the case of net worth, the OLS estimate in column 1 implies an almost zero conditional elasticity, compared to 0.30 in column 2. For house prices, the difference with OLS is also meaningful, but somewhat less extreme because the OLS estimate is not zero. Column 1 gives a conditional elasticity of 0.74 for house prices under OLS, whereas column 2 increases this estimate to 1.03 under 2SLS. As before, these patterns are also consistent with a model in which lending affects both house prices and net worth, but with a larger effect on the former.

The Sargan-Hansen J p-values are all above the usual significance levels. As in the case of the PLS surge, it is remarkable that this is the case even in the lender level specifications of columns 2 and 3 which have around $25,000$ observations. As before, this is strong evidence that we are not missing additional channels. In terms of weak identification, columns 3 and 6 have first stages F that are somewhat below 10. Two things are worth noting. First, the estimates are essentially the same as those in columns 2 and 5, respectively, which have values that are only marginally below 10. Second, exploiting states' APL laws means that the minimum amount of instruments one can employ is three; that is, one more than the amount of endogenous regressors. So it should be noted that columns 3 and 6 have a total of four instruments, and thus it is natural that, with all the fixed effects and controls, the marginal explanatory power added at this point is not enough to compensate for the increased number of instruments. Hence, the fact that the estimates rely on the same type of shocks and are essentially the same as those in columns 2 and 5 means weak identification is not a concern.

Comparison It is also interesting to compare the results that exploit states' APL laws with the previous results exploiting the PLS surge. In general, both set of results point in the same direction: OLS estimates seem severely biased, and the 2SLS effects paint a much more balanced picture for the conditional elasticities of house prices and net worth. Moreover, the exact patterns of the biases depend on the application, but are consistent with each other. In terms of the 2SLS estimates, the effects of house prices tend to be somewhat larger in the case of the APL laws, and the effect of net worth somewhat smaller. However, I should emphasize that, in comparison to the previous estimates, the ones in Table 4 are exploiting variation across a longer span, starting two years earlier and finishing one year later. Hence, it is possible that over the longer period the effect of house prices was larger and the effect of net worth smaller.

Table 5: Lending Growth, 2002-2005

	OLS	2SLS				
	(1)	(2)	(3)	(4)	(5)	(6)
Net Worth Growth	0.360***	1.150***	1.164***	1.004***	1.055***	1.063***
	(0.078)	(0.256)	(0.262)	(0.195)	(0.195)	(0.334)
House Price Growth	1.364***	0.892***	0.889***	0.924***	0.920***	0.678**
	(0.128)	(0.194)	(0.195)	(0.184)	(0.188)	(0.308)
	Instruments					
Dep. Network APO		YES	YES	YES	YES	YES
Elacticity		YES	YES	YES	YES	
Regional APO			YES	YES	YES	YES
Regional elast. (dep)				YES		
Regional elast. (loa)					YES	
Demographics						YES
Kleinbergen-Papp F	-	10.26	8.79	9.07	9.60	3.51
Hansen J (p-value)	-	0.06	0.12	0.02	0.05	0.00
N	620	474	474	474	474	592
R-sq	0.530	0.394	0.388	0.447	0.430	0.377

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table reports estimates of least squares regressions, weighted by the county's population in 2002, relating the county's loans growth, net of the PE estimate $0.090 * APL_{g,2004} \times OCC_{2003} - 0.075 * OCC_{2003} - 0.010 * APL_{g,2004}$, to the county's net worth growth and house price growth. Columns (2)-(6) use the deposit network APO as instrument. Columns (2)-(5) add the housing supply elasticity, columns (3)-(6) add the regional APO, column (4) adds the deposit network elasticity, column (5) instead adds the mortgage loan network elasticity, and column (6) instead adds population shares as of 2002 of Hispanics, Native Americans, Asians, males, and those below age 35. All specifications in the 2SLS panel include $APL_{g,2004}$ and OCC_{2003}. The period considered is 2002-2005. House price growth and the deposit network APO were trimmed at the 5% level. Robust standard errors are below the coefficients in parentheses.

In order to verify this idea and be able to make a more tight comparison between the two shocks, Table 5 presents results that instead rely on the diff-in-diff specifications from Di Maggio and Kermani (2017). These specifications exploit changes over the period 2002-2005. In this way, Table 5 and Table 2 are directly comparable because their results come from the exact same period. With the same logic as before, I now take $\overline{z}_n = APL_{g,2004} \times OCC_{2003}$. As we can see from comparing column 1 to columns 2 through 6, we have the same pattern of Table 2 in the sense that OLS underestimates the effect of net worth and overestimates the effect of house prices. Moreover, the estimates are perfectly in line with the ones obtained when exploiting the PLS surge, which is reassuring. Finally, the same comments on weak identification from Table 4 apply to column 6.

4.3.2 Building the decomposition

PLS surge To complete the decomposition I now turn to equations (12) and (13), and start with the PLS surge. Figure 3 plots the coefficient estimates of regressing the county's house price growth, net worth growth, and lending growth, on the regional and deposit network NCLs. As we can see from the figure, the regional NCL is the relevant shifter for house prices, the deposit network NCL is the relevant shifter for net worth, and, consistent with previous results, both are relevant for lending growth. Thus, for house prices, once one measures the effect of nearby regions, the shocks to regions in their deposit network are not relevant. In contrast, for net worth what matters are the shocks in the network of lenders that connects regions with each other, and shocks to nearby regions are irrelevant outside that network. Because both house prices and net worth matter for lending growth, both the regional and deposit network NCLs have a relevant impact on lending. Table 9 in Appendix B, columns 1, 5 and 9, show the results behind Figure 3.

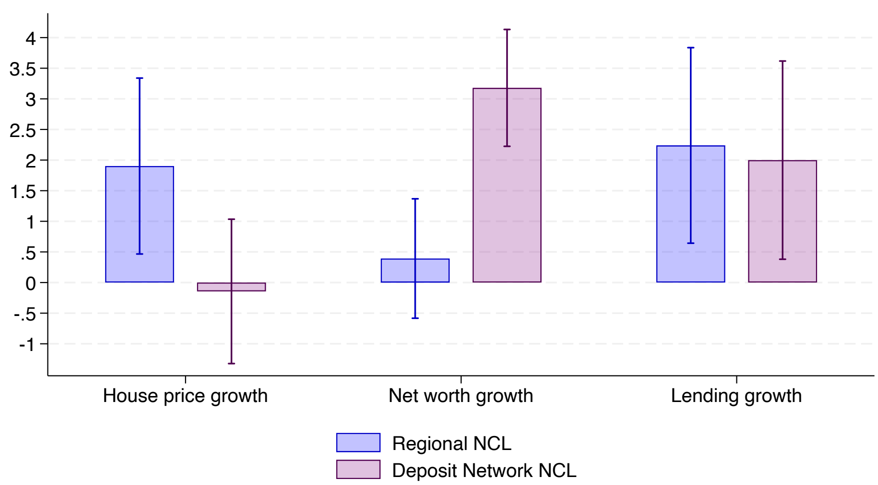


Figure 3: House price, net worth, and lending growth against regional and deposit network NCLs. The figure plot coefficient estimates of regressions of the county's house price growth, net worth growth, and lending growth, net of the partial equilibrium effect of Table 2 column 1, on the regional and deposit network NCLs. The capped lines represent 95% confidence bands.

With the results of Table 9 we now have all the pieces needed to build the decomposition of the global multiplier. Of course, the precise decomposition we ultimately estimate depends on the specifications we choose from the results in this section. There is not one single correct number, as all the pieces involved also have estimation error. At a more fundamental level though, taken together, the results in this section clearly establish that the OLS estimates of, e.g., column 2 in Table 2 are biased. However, the exact magnitude of this bias is difficult to establish incontestably because of the estimation error. Hence, instead of choosing one set of numbers, I will construct two different decompositions that I view as going from more conservative to less conservative, depending on how far we are from the OLS estimates in the first step of the decomposition. Thus, I will say the decomposition is more conservative if it is closer to the one that would obtain if the OLS results were employed, because this implicitly attributes the larger difference between the 2SLS and OLS estimates to sampling variation.

I start with the more conservative approach. For net worth I pick an estimate in the lower range of the ones in Tables 2 through 3 which, rounding to the nearest decimal, is 0.5. For house prices, I take 0.75 which is along the upper range of the estimates. Combining these estimates with the results of Table 9 that include the housing supply elasticity we get:

$$\begin{aligned}\hat{\beta}_{GM} &= 0.75 \times 1.97 + 0.5 \times 2.85 = 2.90 \\ \text{Housing channel} &= (0.75 \times 1.97)\,/2.90 = 51\% \\ \text{FI channel} &= (0.5 \times 2.85)\,/2.90 = 49\%.\end{aligned}$$

For the less conservative approach I take estimates along the upper range for net worth, which is around 1, and along the lower range for house prices, which is around 0.55. With these estimates we get $\hat{\beta}_{GM} = 0.55 \times 1.97 + 1 \times 2.85 = 3.93$, Housing channel $= (0.55 \times 1.97)\,/3.93 = 28\%$ and FI channel $= (1 \times 2.85)\,/3.93 = 72\%$.

States' APL laws I now turn to the decomposition of the shocks that exploit the states' APL laws. Table 6 is the equivalent of Table 9 for this case. As we can see from comparing the three columns, the same pattern holds in the sense that, for the housing channel, the regional APO is the relevant shifter, whereas the deposit network APO is the relevant one for net worth. As before, both variables are relevant for lending.

If we combine the results of Table 6 with the previous 2SLS results from Table 4, for the more conservative approach, we obtain $\hat{\beta}_{GM} = 1 \times 0.5 + 0.3 \times 1.4 = 0.92$, Housing channel $= (1 \times 0.5)\,/0.92 = 54\%$ and FI channel $= (0.3 \times 1.4)\,/0.92 = 46\%$. As we can see from these numbers, the decomposition is remarkably close to the one performed for the PLS surge.

4.4 Summary

To summarize, the results in this section point to a significant amount of amplification, consistent with the results in Mian, Sarto and Sufi (2023). Moreover, they point to both the housing channel and the FI channel contributing meaningfully to this amplification, with

Table 6: House Prices, Net Worth, and Lending, 2000-2006

	$\log(\text{House Price})_{n,t}$	$\log(\text{Net Worth})_{n,t}$	$\log(\text{Loan amount})_{n,t}$
	(1)	(2)	(3)
Regional $APO_{n,t}$	0.565**	0.392	0.643***
	(0.255)	(0.339)	(0.245)
Deposit Network $APO_{n,t}$	0.018	1.421***	0.360**
	(0.126)	(0.427)	(0.143)
		Controls	
County FE, Year FE	YES	YES	YES
APL, OCC, Post Controls	YES	YES	YES
N	4041	9778	9847
R-sq	0.845	0.983	0.993

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of least squares regressions at the county level, weighted by the county's population in 2000, relating the change in the county's (log) house price level, (log) net worth, and the (log) amount of newly originated loans, net of the PE estimate $0.090 * APL_{g,t} \times Post_{2004} \times OCC_{2003} - 0.075 * Post_{2004} \times OCC_{2003} - 0.010 * APL_{g,t} \times OCC_{2003}$, to the regional and deposit network APO variables. All columns include county and year fixed effects, and control for $APL_{g,t}$, $APL_{g,t} \times Post_{2004}$, $OCC_{2003} \times Post_{2004}$, and $APL_{g,t} \times OCC_{2003}$. The sample includes years from 2000 to 2006. The (log) house price level was trimmed at the 1% level, and the deposit network APO at the 5% level. Robust standard errors, clustered at the county level, are below the coefficients in parentheses.

the multiplier split in half in the more conservative estimates. Even more, they are consistent across two natural experiments identified in the literature that exploit very different sources of variation, something which greatly increases the confidence in the decompositions. Thus, whichever was the initial impulse that triggered the credit boom, these results and the consistency for the two distinct natural experiments, make a strong case for both channels having played a major role. This, in turn, suggests that any attempt to curb the magnitude of these episodes must target both the housing market and the financial intermediaries that channel the funds that support the financing process. Finally, there is strong evidence, for both shocks, that there are not alternative amplification channels at play. This reinforces the notion that the emphasis the literature has placed in the housing and FI channels is well placed.

5 Threats to Validity, Heterogeneity and Local multipliers

5.1 Threats to validity

In Section 3.4.1 I discussed the three main threats to identification from the strategy in this paper. In the previous section, I presented a battery of tests based on the Sargan-

Hansen J statistic that address the issue of the channels considered in this paper being a reasonable account for the amplification mechanisms of the credit supply shocks. Although it is impossible to completely rule out other channels, these tests lend strong support to the notion that the housing and FI channels capture the bulk of these spillovers. In this section I present two additional tests of this threat, one for each shock, and then tackle the remaining concerns.

Channels Table 16 in Appendix B performs another test of the channels at play by reestimating the specification of column 4 in Table 2, but now sequentially including house price and net worth growth in the instrument list, i.e., treating them as exogenous, or excluding them from the specification altogether. Column 1 keeps the result form Table 2 for ease of reference. In columns 2 and 3 I include both regressors in the instrument list sequentially. In columns 4 and 5 I exclude them from the regressions altogether, also sequentially. As we can see from the comparison of the Sargan-Hansen J statistics and p-values of column 1 with the values in columns 2 through 5, the p-values decrease from 0.19 in column 1, to essentially zero in any of the other four columns. Thus, this is strong evidence that we are not missing meaningful channels in our specifications. Moreover, regardless of the comparison, the J statistics and p-values of columns 2 through 5 in isolation are evidence that both of the channels considered are indeed endogenous (columns 2 and 3), and that both also play a meaningful role (columns 4 and 5).

Table 17 in Appendix B repeats this exercise for the strategy that exploits the states' APL laws. As we can see from the comparison of column 1 with columns 2 through 5, the same pattern of Table 16 holds. The Sargan-Hansen p-value comes at 0.37 in column 1, and decreases to essentially zero in any of the remaining columns. As before, this is strong evidence that both channels are indeed relevant and endogenous, and that we are not missing additional channels for this shock as well.

Confounding the Credit Supply Shock The simulations presented in Section 3.4.1 show that when the confounder biases upwards both channels, as a demand-side confounder would probably do, the decompositions are very mildly affected. This is because, being a ratio, the effects on each channel are close to cancelling each other out. However, we can go further by exploring the consequences of assuming we can estimate the partial equilibrium effects without bias.

Because the shocks exploited by Mian and Sufi (2021) operate at the bank level, it is highly unlikely that the partial equilibrium effect estimate of Table 2, based on $\hat{\beta}_{pe}$ from Section 3.4, could be affected. This is because for this to happen the confounder would need to vary by lender within a county, in a way that lines up with the supply shock, which is unreasonable. The same logic applies to the shock exploited in Di Maggio and Kermani (2017), for which the partial equilibrium estimates are reproduced in Table 13 below (column 1). This means that the main concern in terms of demand-side confounders is whether the confounder has a general equilibrium effect; i.e., whether in Table 1 we are in the first or second row of the first column. Hence, by comparing the partial equilibrium estimates with the ones that obtain when controlling for house prices and net worth, or the reduced form specifications that include the instruments directly, we can get an indirect test of whether there are such confounders.

Table 12 in Appendix B presents such tests for the case of the PLS surge. Column 1 reproduces the partial equilibrium estimate from Table 2 column 1. Columns 2 and 3 instead replace the county fixed effects with the regional and deposit network NCLs (column 2), and with the net worth and house price growth (estimated via 2SLS, column 3). As we can see from comparing the first row across the three columns, the partial equilibrium effect is essentially unchanged. Under the assumption that the estimate in column 1 is unaffected by demand-side confounders, we would expect specifications in columns 2 and 3 to alter the partial equilibrium estimates if the instruments are picking up demand-side confounders that have general equilibrium effects. Thus, the stability of the partial equilibrium estimates reinforces the notion that there are no such demand-side confounders. Table 13 reiterates this exercise for the case of states' APL laws. As we can see from comparing the partial equilibrium effect in column 1 to those of columns 2 and 3, we again see no meaningful difference in this case.

Network Misspecification The second main threat is related to the network connections that are used to measure the multipliers. Fortunately, Proposition 2 significantly alleviates the concerns on this front, because it establishes, under very weak conditions, that one should be worried about the connections within the network, not the specific weights attached to each connection. Thus, using the deposit network or a loan network is relevant only to the extent that connects the right set of counties with each other. In this regard, Figure 3 and Table 9 present evidence that the regional NCL is the relevant network for house prices, and the deposit network NCL is the relevant network for net worth. Similarly, Table 6 shows that the regional APO is the relevant network for house prices and the deposit network APO is the relevant one for net worth. As with any threat to validity, it is difficult to completely dismiss any concern, but these results are strong evidence that the connections we are using are the relevant ones, and Proposition 2 says the exact weight attached to each connection is irrelevant.

Additional robustness checks Section B in the Appendix present additional robustness checks. In Table 18 we rerun all the specifications of Table 2, but using the mortgage loan weights within the county to construct the county's net worth. As we can see from the comparison with Table 2, the patterns are exactly the same. The point estimates on net worth are slightly higher, but the OLS estimates are also higher. Moreover, the Sargan-Hansen p-values are even higher in the first three columns, now rejecting the null in all those columns at any conventional level of significance. All the Kleinbergen-Papp Fs are also well above the conventional thresholds for weak instruments.

Because Table 5 does not rely on county or county-agency fixed effects, as the specifications in Table 4 do, it is interesting to look at other variables that might be relevant for the period 2002-2005. Following Di Maggio and Kermani (2017), we explore them in Table 10. As we can see from the comparison with Table 5 results are essentially the same, even when including changes during the period of important variables, such as population or income growth.

5.2 Heterogeneity

2SLS results In terms of our 2SLS estimates, the results presented in Section 4.3.1 point to heterogeneous effects not being a particularly salient feature, if present. In that section, we estimated the same conditional elasticities for a very extensive and diverse set of instruments. These sets went from instruments that exploited variation tied to the PLS surge, instruments that exploited states' APL laws, up to instruments that relied exclusively on the housing supply elasticities. Even thought there were was some variability, the conditional elasticities were all in line with each other.

PLS surge In Table 9, columns 2, 6, and 10, we look at heterogeneity in the case of the PLS surge shock. Consistent with the results in Mian et al. (2023), and the model in Section 2, the regional NCL has a much larger impact on house prices in counties with inelastic housing supplies, as evidenced by the significant coefficients for the interaction in column 2. Column 6 shows the regional NCL having an impact on net worth in very inelastic counties, which would be reasonable because many of the lenders in our sample are smaller, more local, and exposed to the local housing market. Column 10 shows these results are also consistent with the heterogenous impact of the regional NCL on lending.

States' APL laws In Table 11, columns 2, 4, and 6, we look for heterogenous effects in the case of the states' APL laws. Consistent with the previous results, column 2 shows that the regional APO also has a much larger effect on counties with inelastic housing supplies.

Column 4 shows it also seems to have an impact on net worth in such counties, but the relations are not statistically significant. Consistent with these results, column 6 shows the regional APO has a much larger effect in counties with inelastic housing supplies.

Updating the decompositions I now use the margin of the housing supply elasticity to update the decompositions of Section 4.3.2 across counties with high vs low housing supply elasticities, in the case of the PLS surge. To that end, columns 3-4 and 7-8 of Table 9 control for the housing supply elasticity and split the samples between counties with high housing supply elasticity, with a measure above 1, and counties with a low housing supply elasticity (below 1). The sample sizes are not exactly the same for house prices and net worth, but this is equivalent to approximately splitting observations around the counties in the lowest decile of the housing supply elasticity distribution. Consistent with the previous results the regional NCL has a much larger effect in counties with very inelastic housing markets, and again it seems to have an impact on the net worth in those counties, although it is difficult to know with certainty given the small sample size. Columns 3 and 4 show that the deposit network NCL is irrelevant both in counties with inelastic supplies and in counties with high housing supply elasticities. This is consistent with the fact that the regional NCL dominates for house price growth. Moreover, columns 7 and 8 show that the deposit network NCL is relevant, and with practically the same effect, in both types of counties. This is consistent with the idea that, for lenders' net worth, the relevance of the supply shocks through their networks do not depend on the housing supply elasticities of the counties in which they operate. The lower statistical significance in column 7 compared to that of column 8 is just a feature of the ten-fold smaller sample size.

Housing Supply Elasticity	Housing Channel	FI Channel	$\hat{\beta}_{GM}$
Low	66%	34%	4.22
Average	51%	49%	2.90
High	29%	71%	1.99

Table 7: Different decompositions of $\hat{\beta}_{GM}$ as a function of the housing supply elasticity.

Using these estimates, Table 7 updates the decomposition from Section 4.3.2 for the more conservative approach. Because the only clear heterogeneous effects happened for house price growth, the only difference in the estimates comes from the coefficients on the regional NCL of columns 3-4 of Table 9. As we can see from the first row, the housing channel accounts for 66% of the amplification observed in counties with very inelastic housing supplies. Moreover, the multiplier in those regions, at 4.22, is much larger than the average of 2.90. In contrast, in the last row we see that the housing channel accounts for only 29% in counties with a very elastic housing supply, and the multiplier in those counties decreases to 1.99. The implications for the FI channel are the converse of the housing channel, of course. Thus, they highlight that the reason we still observe a multiplier of 1.99 in high elasticity areas is partly due to housing, i.e. those areas have more elastic housing supplies but there is still some rigidity, but mostly due to the FI channel. Lenders' balance sheets are still powerful enough as transmitters of the general equilibrium spillovers across regions that the multiplier is still economically significant, with roughly 70% coming from the FI channel.

5.3 Local multipliers

The final task we tackle in this section is to empirically assess the difference between the local and global regional multipliers. So far we have focused on the global multiplier, but it is interesting to estimate the local multiplier as well, and compare the results so far with empirical strategies that just target the latter.

PLS surge Table 19 in Appendix B estimates a specification similar to those in Table 9, but now focusing on the difference between the two regional multipliers. To that end, Table 19 uses the own county's NCL in 2002, and modifies the deposit network NCL by excluding the county's own NCL from the measure, so that both variables are then "disjoint" in terms of the NCL loadings. In the external deposit network NCL we readjust the weights so that they sum to one, but we redistribute the weight of the own county's NCL proportionally among the remaining counties in the network. The estimate of 2.14 in column 1 is the local regional multiplier. The difference between the local and the global multipliers is coming from the 1.26 in the second row. The sum of the two rows gives 3.4 which is in line with the estimates for the global multiplier of Table 7.

States' APL laws Table 20 in Appendix B repeats the exercise for the case of the states's APL laws. Because the only overlap between the regional and deposit network APO in this case is for the own county, we use those variables for the split. The estimate of 0.64 in column 1 is the local regional multiplier. The estimate of 0.36 on the deposit network APO in column 1 is the difference between the local and global regional multipliers.

Comparison In both natural experiments the local regional multipliers account for the bulk of the amplification observed at the regional level, which is consistent with the results in Mian, Sarto and Sufi (2023). Moreover, it is remarkable that, in both cases, the breakdown has around 65% of the global multiplier coming from the local one. In the case of the PLS surge, the breakdown is 63% = 2.14/3.4; in the case of the states' APL laws it is 64% = 0.64/1. The consistency of these results also contribute to the confidence in the previous results overall.

Finally, column 2 of Tables 19 and 20, show what happens if we omit the external deposit network. As discussed in Section 3.4, as long as the correlation of the credit supply shocks is low within each county's network, the strategy for estimating the local multipliers is more robust than the one for the global multiplier because it avoids taking a stand on the nature of the network that connects regions with each other.

6 Conclusion

Two main main contributors were identified as crucial for the credit boom that let to the global financial crisis. A housing boom and the relaxation of credit constraints that resulted in a massive channeling of funding to the residential mortgage market. Although there is consensus that both forces played an important role, their relative contributions are less clear. This paper provides a novel empirical strategy to shed light on this issue. First, I estimate the conditional elasticities of housing and the lending capacity of financial intermediaries on lending. Second, I decompose the effects of two credit supply shocks identified in the literature between the housing channel and the FI channel. Overall, results are consistent across the two shocks and point towards both channels playing a significant role. In the more conservative specifications, their role is split in half. In the less conservative specifications, the FI channel plays a larger role. The housing channel accounts for 66% of the effects in regions with a more inelastic housing supply, while the FI channel helps understand why, even in regions with very elastic housing supplies, there are still significant amounts of amplification. In the latter regions the FI channel accounts for 71% of the observed effects.

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Internet Appendix

For Online Publication

A Proofs

Proposition 1

Proof. We first show existence and uniqueness. It is straightforward to show that under Assumptions 4 and 5 we have:

$$
\begin{aligned}
l_{i1} &= \theta_i\left(W_0\right) A_{i1}\left[\frac{\left(A_{i0}+q^d+q^m \varsigma_{i0}\right) d_{i0}^E-l_{i0}}{\chi_{i1}^E+q^d+q^m \varsigma_{i1}-\theta_i\left(W_0\right) A_{i1}}\right] \\
d_{i1}^E &= \frac{\left(A_{i0}+q^d+q^m \varsigma_{i0}\right) d_{i0}^E-l_{i0}}{\chi_{i1}^E+q^d+q^m \varsigma_{i1}-\theta_i\left(W_0\right) A_{i1}}=m_{i1}^E / \varsigma_{i1},
\end{aligned}
$$

for entrepreneurs, together with:

$$
\begin{aligned}
d_{i1}^B &= \frac{\varrho_{i1}^d}{q^d+\chi_{i1}^B} \\
m_{i1}^B &= \frac{\varrho_{i1}^m}{q^m}
\end{aligned}
$$

for banks. Let us define:

$$
\phi_d\left(q^d, q^m\right)=\sum_{i=1}^I\left[\frac{\left(A_{i0}+q^d+q^m \varsigma_{i0}\right) d_{i0}^E-l_{i0}}{\chi_{i1}^E+q^d+q^m \varsigma_{i1}-\theta_i\left(W_0\right) A_{i1}}+\frac{\varrho_{i1}^d}{q^d+\chi_{i1}^B}\right],
$$

and let us take

$$
\begin{aligned}
\varrho_{i1}^d &> \max \left\{\frac{d_{i0}^E\left[\chi_{i1}^E+1+\varsigma_{i1}\right]}{\left[\chi_{i1}^E-\left(\overline{\theta}_i\right)^{-1 / \psi_i} A_{i1}\right]^2\left(1+\chi_{i1}^B\right)^{-2}}, \begin{array}{c}\frac{\left[\chi_{i1}^B\left(1+\chi_{i1}^B\right)\right]\left(A_{i0}+1+\varsigma_{i0}\right) d_{i0}^E-l_{i0}}{\chi_{i1}^E+1+\varsigma_{i1}-\left(\overline{\theta}_i\right)^{-1 / \psi_i} A_{i1}} \\ -\frac{\left[\chi_{i1}^B\left(1+\chi_{i1}^B\right)\right]\left(A_{i0} d_{i0}^E-l_{i0}\right)}{\chi_{i1}^E-\theta_i\left(l_0\right) A_{i1}}\end{array}\right\} \\
\varrho_{i1}^m &> \frac{\left(\overline{\eta}+\varsigma_{i0}\right) \varsigma_{i1} d_{i0}^E\left[\chi_{i1}^E+1+\varsigma_{i1}\right]-\left[A_{i0} d_{i0}^E \varsigma_{i1}-l_{i0} \varsigma_{i1}\right]\left\{\varsigma_{i1}-\theta_i^{\prime}\left(l_0\right)\left[\overline{\eta} d_0^B+m_0^B\right] A_{i1}\right\}}{\left[\chi_{i1}^E-\left(\overline{\theta}_i\right)^{-1 / \psi_i} A_{i1}\right]^2},
\end{aligned}
$$

together with

$$d_0^B < \min_i \left\{ \left[\theta_i'(l_0)\right]^{-1}, \frac{\varsigma_{i1}}{\theta_i'(l_0) A_{i1}} \left[\varsigma_{i1} + \frac{\sum_{i=1}^I \frac{d_{i0}^E \varsigma_{i0}\left[\chi_{i1}^E + 1 + \varsigma_{i1}\right]}{\left[\chi_{i1}^E - \left(\overline{\theta}_i\right)^{-1/\psi_i} A_{i1}\right]^2}}{\sum_{i=1}^I \frac{\varrho_{i1}^d}{\left(1+\chi_{i1}^B\right)^2} - \frac{d_{i0}^E\left[\chi_{i1}^E + 1 + \varsigma_{i1}\right]}{\left[\chi_{i1}^E - \left(\overline{\theta}_i\right)^{-1/\psi_i} A_{i1}\right]^2}} \right]^{-1} \right\}$$

$$m_0^B < \min_i \left\{ \varsigma_{i1}\left[\theta_i'(l_0)\right]^{-1}, \frac{\varsigma_{i1}}{\theta_i'(l_0) A_{i1}} - \frac{d_0^B \sum_{i=1}^I \frac{d_{i0}^E \varsigma_{i0}\left[\chi_{i1}^E + 1 + \varsigma_{i1}\right]}{\left[\chi_{i1}^E - \left(\overline{\theta}_i\right)^{-1/\psi_i} A_{i1}\right]^2}}{\sum_{i=1}^I \frac{\varrho_{i1}^d}{\left(1+\chi_{i1}^B\right)^2} - \frac{d_{i0}^E\left[\chi_{i1}^E + 1 + \varsigma_{i1}\right]}{\left[\chi_{i1}^E - \left(\overline{\theta}_i\right)^{-1/\psi_i} A_{i1}\right]^2}} \right\},$$

where

$$\overline{\eta} = \frac{\sum_{i=1}^I \frac{d_{i0}^E \varsigma_{i0}\left[\chi_{i1}^E + 1 + \varsigma_{i1}\right] - \left[A_{i0} d_{i0}^E - l_{i0}\right]\left(\varsigma_{i1} - \theta_i'(l_0) m_0^B\right)}{\left[\chi_{i1}^E - \left(\overline{\theta}_i\right)^{-1/\psi_i} A_{i1}\right]^2}}{\sum_{i=1}^I \frac{\varrho_{i1}^d}{\left(1+\chi_{i1}^B\right)^2} - \frac{d_{i0}^E\left[\chi_{i1}^E + 1 + \varsigma_{i1}\right] - \left[A_{i0} d_{i0}^E - l_{i0}\right]\left(1 - \theta_i'(l_0) d_0^B\right)}{\left[\chi_{i1}^E - \left(\overline{\theta}_i\right)^{-1/\psi_i} A_{i1}\right]^2}}.$$

Because of the first lower bound on ϱ_{i1}^d and the first upper bound on d_0^B we have $\frac{\partial \phi_d\left(q^d, q^m\right)}{\partial q^d} < 0$. Moreover, because of Assumption 5 we have that $\partial d_{i1}^E / \partial q^d > 0$, and the second lower bound on ϱ_{i1}^d implies $\phi_d(1,1) < \phi_d(0,0)$. This means any $\overline{D} \in \left(\phi_d(1,1), \phi_d(0,0)\right)$ gives a unique equilibrium in the land market with $q^{d*}(q^m) \in (0,1), \forall q^m \in [0,1]$. Furthermore, from the implicit function theorem and Assumption 5 we have $\partial q^{d*}(q^m)/\partial q^m > 0$, and from the first upper bound of m_0^B we have $\partial q^{d*}(q^m)/\partial q^m \leq \overline{\eta}$.

Taken together, the second upper bounds of m_0^B and d_0^B, and the lower bound on ϱ_{i1}^m, imply the function:

$$\phi_m(q^m) = \sum_{i=1}^I \left[\frac{\left(A_{i0} + q^{d*}(q^m) + q^m \varsigma_{i0}\right) d_{i0}^E - l_{i0}}{\chi_{i1}^E + q^{d*}(q^m) + q^m \varsigma_{i1} - \theta_i\left[W_0\left(q^{d*}(q^m)\right)\right] A_{i1}} \varsigma_{i1} + \frac{\varrho_{i1}^m}{q^m} \right]$$

is decreasing in q^m, $\partial \phi_m(q^m)/\partial q^m < 0$. In addition, we have that:

$$\lim_{q^m \to 0} \phi_m(q^m) = \infty$$

$$\phi_m(1) = \sum_{i=1}^I \left[\frac{\left(A_{i0} + q^{d*}(1) + \varsigma_{i0}\right) d_{i0}^E - l_{i0}}{\chi_{i1}^E + q^{d*}(1) + \varsigma_{i1} - \theta_i\left[W_0\left(q^{d*}(1)\right)\right] A_{i1}} \varsigma_{i1} + \varrho_{i1}^m \right],$$

so any $\overline{M} \in \left(\phi_m(1), \infty\right)$ gives a unique interior equilibrium. Moreover, note that the consumption of entrepreneurs is necessarily strictly positive, and we can always choose e large enough for banks' consumption to be strictly positive as well. Also, note that both land and machines investments are strictly positive.

We now move to characterize the amplification effects. Given that $l_{i1} = \theta_i(W_0) A_{i1} d^E_{i1}$ we have that:

$$l^*_{i1}\left(\psi, q^d, W_0\right) = \theta_i(W_0) A_{i1} \left[\frac{\left(A_{i0} + q^d\left(1 - \frac{d^B_0}{m^B_0}\varsigma_{i0}\right) + W_0\frac{\varsigma_{i0}}{m^B_0} - \frac{l_0}{m^B_0}\varsigma_{i0}\right) d^E_{i0} - l_{i0}}{\chi^E_{i1} + q^d\left(1 - \frac{d^B_0}{m^B_0}\varsigma_{i1}\right) + W_0\frac{\varsigma_{i1}}{m^B_0} - \frac{l_0}{m^B_0}\varsigma_{i1} - \theta_i(W_0) A_{i1}}\right],$$

where:

$$\theta_i(W_0) = \left[\overline{\theta}_i + \frac{e^{-W_0}}{W_0}\right]^{-\frac{1}{\psi}}.$$

Thus, $\partial\theta_i(W_0)/\partial\psi > 0$ implies $\partial l^*_{i1}/\partial\psi > 0$. Moreover, Assumption 5 and the second upper bound on d^B_0 imply $\partial l^*_{i1}/\partial q^d > 0$, and Assumption 5 together with

$$\frac{\partial l^*_{i1}}{\partial W_0} = \frac{\partial\left[\theta_i(W_0) A_{i1} d^E_{i1}\right]}{\partial q^m}\frac{1}{m^B_0}$$

imply $\partial l^*_{i1}/\partial W_0 > 0$. Finally, because $\partial\phi_m(q^m, \psi)/\partial\psi > 0$, where we make explicit the dependance of $\phi_m(q^m)$ on ψ, we have $dq^m/d\psi > 0$. Thus, together with $\partial q^{d*}(q^m)/\partial q^m > 0$ this implies $dq^d/d\psi > 0$. $dW_0/d\psi > 0$ then follows from $W_0 = q^d d^B_0 + q^m m^B_0 + l_0$. ■

Proposition 2

Proof. First, note that:

$$\begin{aligned}
&\frac{1}{N}\sum_n\left(\alpha z_{\mathcal{N}(n)} + \sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon^z_c\right)\sum_{c\in\mathcal{N}(n)}\left\{\widetilde{w}_{nc} - \left(\sum_b\omega_{nb}l_{cb}\right)\right\}\left(\alpha z_{\mathcal{N}(n)} + \varepsilon^z_c\right)\\
&= \frac{1}{N}\sum_n\left(\alpha z_{\mathcal{N}(n)} + \sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon^z_c\right)\left\{\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon^z_c - \sum_{c\in\mathcal{N}(n)}\left(\sum_b\omega_{nb}l_{cb}\right)\varepsilon^z_c\right\}\\
&= \frac{1}{N}\sum_n\left(\alpha z_{\mathcal{N}(n)} + \sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon^z_c\right)\left(\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon^z_c\right)\\
&- \frac{1}{N}\sum_n\left(\alpha z_{\mathcal{N}(n)} + \sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon^z_c\right)\left[\sum_{c\in\mathcal{N}(n)}\left(\sum_b\omega_{nb}l_{cb}\right)\varepsilon^z_c\right].
\end{aligned}$$

For the first term we have:

$$\frac{1}{N}\left|\sum_{n}\left(\alpha z_{\mathcal{N}(n)}+\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)\left(\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)\right|$$
$$\leq\sqrt{\frac{1}{N}\sum_{n}\left(\alpha z_{\mathcal{N}(n)}+\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)^2}\sqrt{\frac{1}{N}\sum_{n}\left(\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)^2},$$

and note that:

$$\begin{aligned}
&\mathbb{E}\left|\frac{1}{N}\sum_{n}\left(\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)^2\right|\\
&=\frac{1}{N}\sum_{n}\mathbb{E}\left(\sum_{c\in\mathcal{N}(n)}\sum_{j\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\widetilde{w}_{nj}\varepsilon_j^z\right)\\
&=\frac{1}{N}\sum_{n}\mathbb{E}\left(\sum_{c\in\mathcal{N}(n)}\left\{\widetilde{w}_{nc}^2\left(\varepsilon_c^z\right)^2+\sum_{j\in\mathcal{N}(n),j\neq c}\widetilde{w}_{nc}\varepsilon_c^z\widetilde{w}_{nj}\varepsilon_j^z\right\}\right)\\
&=\frac{1}{N}\sum_{n}\left(\mathbb{E}\left[\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}^2\left(\varepsilon_c^z\right)^2\right]+\sum_{c\in\mathcal{N}(n)}\sum_{j\in\mathcal{N}(n),j\neq c}\mathbb{E}\left\{\mathbb{E}\left[\varepsilon_c^z\varepsilon_j^z\middle|\widetilde{w}_{nc}\widetilde{w}_{nj}\right]\widetilde{w}_{nc},\widetilde{w}_{nj}\right\}\right)
\end{aligned}$$

$$\begin{aligned}
&=\frac{1}{N}\sum_{n}\mathbb{E}\left[\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}^2\left(\varepsilon_c^z\right)^2\right]\\
&=\frac{1}{N}\sum_{n}\mathbb{E}\left[\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}^2\mathbb{E}\left\{\left(\varepsilon_c^z\right)^2\middle|\widetilde{w}_{nc}^2\right\}\right]\\
&=\frac{1}{N}\sum_{n}\mathbb{E}\left[\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}^2\sigma_{\varepsilon^z}^2\right]\\
&=\frac{\sigma_{\varepsilon^z}^2}{N}\sum_{n}\sum_{c\in\mathcal{N}(n)}\mathbb{E}\left[\widetilde{w}_{nc}^2\right]\leq\frac{\sigma_{\varepsilon^z}^2}{N}\sum_{n}\sum_{c\in\mathcal{N}(n)}\frac{K}{M^2}=\frac{\sigma_{\varepsilon^z}^2K}{M}\underset{M\to\infty}{\longrightarrow}0.
\end{aligned}$$

Hence:

$$\frac{1}{N}\left|\sum_{n}\left(\alpha z_{\mathcal{N}(n)}+\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)\left(\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)\right|\leq O_p\left(1\right)o_p\left(1\right)=o_p\left(1\right).$$

With the same arguments we have:

$$\left|-\frac{1}{N}\sum_{n}\left(\alpha z_{\mathcal{N}(n)}+\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)\left[\sum_{c\in\mathcal{N}(n)}\left(\sum_{b}\omega_{nb}l_{cb}\right)\varepsilon_c^z\right]\right|=o_p\left(1\right),$$

and thus:

$$\frac{1}{N}\sum_{n}\left(\alpha z_{\mathcal{N}(n)}+\sum_{c\in\mathcal{N}(n)}\widetilde{w}_{nc}\varepsilon_c^z\right)\sum_{c\in\mathcal{N}(n)}\left\{\widetilde{w}_{nc}-\left(\sum_{b}\omega_{nb}l_{cb}\right)\right\}\left(\alpha z_{\mathcal{N}(n)}+\varepsilon_c^z\right)=o_p\left(1\right).$$

■

B Additional Material and Results

B.1 Additional material on the model

Two additional assumptions will be useful in guaranteeing the existence and uniqueness of the equilibrium, along with the amplification of credit supply shocks through the price of land and the balance sheets of lenders in the region. First, I impose some restrictions on A_{i1} and l_{i0} and on the fruit requirement per unit of land, χ_{i1}^E.

Assumption 4. *The fruit requirement per unit of land, χ_{i1}^E, satisfies*:

$$\chi_{i1}^E>\overline{\theta}_i^{-1/\psi_i}A_{i1},$$

and the values of A_{i1} and l_{i0} satisfy:

$$A_{i1}>\chi_{i1}^E+1+\varsigma_{i1}$$
$$l_{i0}<A_{i0}d_{i0}^E.$$

The first condition guarantees that the down payment entrepreneurs need to make is always positive, so that some liquidity on their part is essential. The second condition makes sure entrepreneurs are productive enough that they will always want to invest in land and machines. The third condition is sufficient for entrepreneurs' to start with positive net worth regardless of the price of the assets. Because they always make a net gain by investing, this means they will seek as much leverage as possible from banks, making (1) bind.[24] Due to this feature I will refer to the equilibrium as a credit constrained equilibrium.

[24] See Mian et al. (2023) for a more detailed description of these conditions.

Second, I assume that the initial debt level, l_{i0}, is sufficiently high.

Assumption 5. $d_{i0}^{E}\left\{A_{i0}-\left(\chi_{i1}^{E}-\theta_{i}A_{i1}\right)\right\}<l_{i0}$ *and* $\varsigma_{i0}=\varsigma_{i1}$.

The first condition makes sure that leverage is high enough for entrepreneurs that when there is an increase in the price of land or machines the positive effect over their net worth dominates the increase in the down payment they face, increasing their demand for the assets. The second condition makes sure the same restriction applies to both land and machines.

B.2 Relationship with Aggregate Multipliers

In deriving the partial equilibrium effect we held constant the regional and aggregate equilibrium objects. In deriving the regional multipliers we held constant the aggregate equilibrium objects. However, because I have simplified the notation by starting from the partialed out system with respect to the time fixed effects, the fact that in deriving the three causal effects we held constant the aggregates was not made explicit. If we made the last layer of aggregation explicit, we could define the aggregate multipliers, which would take the measured effect of the shocks at the regional level to their total effects. For a derivation along these lines that makes all these points explicitly, and discusses further issues on the relationship of aggregate multipliers with regional multipliers, see Mian, Sarto and Sufi (2023). The only point I reemphasize here is that, as the model in Section 2 makes clear, there are many instances in which the general equilibrium effects we are interested in from a macro perspective do not materialize at the highest possible level of aggregation, allowing us to study them with tools such as those developed in this study and Mian, Sarto and Sufi (2023).

B.3 Decomposition from a Public Policy Perspective

As I have emphasized in the introduction of Section 3.2, focusing on estimating the causal effects from systems such as (5)-(8) is an advantage because it allows us to avoid taking a stand on the specifics of the underlying model, which could inject bias in our estimates if done incorrectly. However, we should keep in mind that the interpretation of the causal effects derived in the previous paragraphs is useful for either small changes in the variables, or to understand how credit was amplified in financial markets during the boom that led to the GFC. In particular, it does not mean that if we completely shut down one of the channels overnight the amplification would decrease to the level of the remaining channel.

To illustrate, suppose in the model of Section 2 we change the lending constraint to:

$$l_{i1} \leq \psi_i \left(q^d d_{i0}^B + q^m m_{i0}^B + l_{i0} \right),$$

and suppose regulators, interested in decreasing the amount of amplification, impose that banks sell their mortgages by packaging and selling on balance sheet loans and selling their MBS holdings.[25] Taking (10) at face value, one would think that the amplification would now be reduced to $\widetilde{\beta}_{GM} = \sum_{c=1}^{N} \partial g_{nw} (.) / \partial \overline{z}_c$. However, this is not true because a Lucas critique would apply in this case. Changing the rules of what banks can and cannot hold in their balance sheet would certainly affect both channels of amplification. The system (5)-(8) is structural against policies that are contained in the system, and for changes that are not as large as regime shifts. Both of these properties would be violated if banks were forced to offload their exposure to the housing market, because the policy is not a small shift, and because it is not explicitly addressed in (5)-(8). To analyze such a change one would need to modify the motivating model and re-derive a structural system from it, likely focusing on the non-linear version in that case. That is, the machinery developed in the previous paragraphs is not geared towards studying this policy, so there would be shortcomings from applying it to a different question.

However, even though, understandably, the machinery in the previous paragraphs should change, there is a sense in which it would still be very useful as a guide, even for these different questions. The reason is that, although we know the remaining channel would be affected, we can be very confident that a policy that reduces one of the channels is very likely to reduce the other one as well. This is because of the strategic complementarities that are built into models such as the one in Section 2. Hence, the previous machinery would still be useful to decide, e.g., which channel to attack first, knowing that is difficult to predict the exact change based solely on these estimates.

Finally, there is the issue of which multiplier, β_{LM} or β_{GM}, and accompanying decomposition, should we be interested in. The answer is that probably both are always of interest, in the sense that one can view β_{LM} as a further decomposition of β_{GM}, one in which instead of splitting the effects across channels, as defined above, we split them in terms of within-region shocks vs between-region shocks. From this perspective it is always of interest to know both quantities. Of course, if, for example, the policy or shock under study affects only the cross-sectional units in one region, the quantity one is interested in is β_{LM}, regardless of what happens between regions. Under strategic complementarities across regions, β_{GM} would actually overstate the true amount of amplification in this case. If instead the

[25] In reality for some mortgages, such as jumbo loans, this might be harder; for the sake of the argument I assume banks can offload all their exposure to the housing market.

policy or shock is global, one is drawn to β_{GM}. However, as I highlighted before, estimating β_{GM} reliably might be harder in some instances, and this is another consideration that comes into play.

B.4 Additional results

B.4.1 Simulations

Network Misspecification To study the network misspecification concern, I simulate system (5)-(8) with the following parameter choices: I use $N = 300, 1000, 2000, 3000$ to match setups that have MSA or commuting zone level data ($N = 300$ or $N = 1,000$), or county level data ($N = 3,000$). Because I is inessential, I use $I = 3$ to make simulations lighter. Moreover, based on the results of Section 4 I set $\left(\beta^{PE}, \gamma_P, \gamma_W\right) = (0.63, 1.97, 2.85)$, along with $\left(\phi_P, \phi_W\right) = (0.75, 0.5)$. I also set $\varepsilon_{in} = \epsilon_{in}^{y} + d_n$, $\nu_n^P = \epsilon_{in}^P + d_n$, and $\sum_b \omega_{nb} \nu_b^W = \epsilon_{in}^W + d_n$, where $\epsilon_{in}^{y}, \epsilon_{in}^P, \epsilon_{in}^W$ and d_n are $i.i.d.$ with $\epsilon_{in}^{y}, \epsilon_{in}^P, \epsilon_{in}^W, d_n \sim N(0, 1/2)$. I also set $z_{ic} = z_{\mathcal{N}(c)} + \xi_{in}$, where $z_{\mathcal{N}(c)}$ and ξ_{in} are $i.i.d.$ with $z_{\mathcal{N}(c)}, \xi_{in} \sim N(0,1)$, and I use $N/20$ groups to draw $z_{\mathcal{N}(c)}$.

I also generate true weights $\sum_b \omega_{nb} l_{cb}$ as random uniforms that sum to one along the groups $\mathcal{N}(c)$, and repeat the process to generate another draw of false weights in the same fashion. For the 20% incorrect connections panel below, I take the false weights and, for each region in each group, I further move the last four weights (4/20 = 20%) to regions outside their network (in particular, to the next group, but this is irrelevant and just for convenience). Thus, in this panel, the weights are all wrong for the 80% of regions that should receive strictly positive weight, but there is also a 20% of the group that does not receive a weight and that 20% mass goes instead to regions outside the network (which should not receive strictly positive weights).

Simulation results, based on 1000 repetitions, are presented in Table 14. Panel A serves as a reference, and shows the results when we use the correct network, meaning correct set of connections and weights assigned to each link. Panel B shows what happens if we maintain the correct set of connections in the network, but we use a completely random set of weights for each link. Panel C shows what happens if, for each region in Panel B, we also mistakenly shift 20% of their connections to outside regions that do not belong in their network.

As we can see from Table 14, Panels A and B are almost indistinguishable. This is true even for the smaller sample size row of $N = 300$. Thus, in line with the results in Proposition 2, as long as we are using the correct set of connections, the weights assigned to each link are irrelevant, even with smaller sample sizes. Given that all the empirical results in this study feature at least around double the lowest sample size of Table 14, these simulations, along with Proposition 2, significantly alleviate any concern regarding network misspecification. In Panel C we see that misspecifying the connections in the network by 20% does inject bias, particularly in $\hat{\beta}_{GM}$, which now is estimated at around 3.1 (whereas $\beta_{GM} = 2.9$). However, even in this case, columns 9 and 10 show that the bias introduced in the decomposition is fairly small, with the FI channel share being estimated at around 53% (49% being the true share), and the housing channel at around 47% (51% being the true share). Hence, even if one fifth of the connections are misspecified, results are still very close for the decomposition.

Confounding the Credit Supply Shock To study the impact of confounding the credit supply shock on the decomposition, I use the same system and parameter choices of Table 14 Panel A with the following differences: I set $z_{ic} = z_{\mathcal{N}(c)} + \xi_{in} + \sqrt{1/2}d_n$, $\varepsilon_{in} = \epsilon^{y}_{in}$, $\nu^P_n = \epsilon^P_{in} + \sqrt{1/4}d_n$, and $\sum_b \omega_{nb}\nu^W_b = \epsilon^W_{in} + d_n$, where now $d_n \sim N(0,1)$ and the rest of the values are as before.

Simulation results, based on 1000 repetitions, are presented in Table 15. Panel A serves as the reference: I set $z_{ic} = z_{\mathcal{N}(c)} + \xi_{in}$, so there is no confounding shock in that case. Going from panel A to B keeps everything unchanged with the exception that, in Panel B, $z_{ic} = z_{\mathcal{N}(c)} + \xi_{in} + \sqrt{1/2}d_n$.

Comparing Panels A and B we see that, similarly to Panel C of Table 14, the confounder biases upwards $\hat{\beta}_{GM}$, with an estimated value around 3.28 (when $\beta_{GM} = 2.9$). However, as in that case, the bias in the decomposition turns out to be mild. The FI channel share is estimated at around 45% (49% being the true share), and the housing channel at around 55% (51% being the true share). The reason for this is that both the FI channel and the housing channel, columns 5 through 8, are biased upwards, with the housing channel more severely affected. Because the decomposition is based on a ratio, the effect on it is much smaller than the one on the channels or on $\hat{\beta}_{GM}$.

B.4.2 Additional Tables

Table 8: Lending Growth, 2002-2005

	OLS	2SLS		OLS	2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)
NCL 2002	0.646**	0.600*	0.613*	0.646**	0.600*	0.613*
	(0.316)	(0.322)	(0.321)	(0.314)	(0.320)	(0.318)
Net Worth Growth	0.315***	0.937***	0.707***	0.315***	0.937***	0.707***
	(0.083)	(0.225)	(0.195)	(0.103)	(0.261)	(0.222)
House Price Growth	0.924***	0.535**	0.546***	0.924***	0.535**	0.546**
	(0.148)	(0.213)	(0.197)	(0.186)	(0.261)	(0.244)
	Instruments					
Regional NCL		YES	YES		YES	YES
Deposit network NCL		YES	YES		YES	YES
Elasticity		YES	YES		YES	YES
Regional NCL × Elast.			YES			YES
Regional elast. (dep)			YES			YES
Cluster	BHC	BHC	BHC	C & BHC	C & BHC	C & BHC
Kleinbergen-Papp F	-	661.88	471.07	-	30.18	20.79
Hansen J (p-value)	-	0.47	0.00	-	0.57	0.01
N	55068	45638	45638	55068	45638	45638
R-sq	0.092	0.083	0.087	0.092	0.083	0.087

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table reports estimates of least square regressions, weighted by the lending share in the county interacted with the county's 2002 population, relating the lender's loans growth to their NCL as of 2002, and the county's net worth growth and house price growth. Columns (2), (3), (5) and (6) use the regional and deposit network NCLs, as well as the housing supply elasticity, as instruments. Columns (3) and (6) add the regional NCL interacted with the housing supply elasticity, and the deposit network elasticity. The period considered is 2002-2005. Net worth growth was trimmed at the 5% level. Robust standard errors, clustered at the bank holding company level in columns (1) through (3) and at the county and bank holding company levels in columns (4) through (6), are below the coefficients in parentheses.

Table 9: House Prices, Net Worth, and Lending Growth, 2002-2005

	House Price Growth				Net Worth Growth				Lending Growth	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Regional NCL	1.903***	4.266***	3.734**	0.756	0.393	2.222***	2.394	-0.155	2.239***	5.134***
	(0.732)	(0.822)	(1.456)	(0.726)	(0.497)	(0.769)	(1.447)	(0.679)	(0.814)	(1.520)
Deposit network NCL	-0.144	0.129	-0.501	-0.211	3.179***	3.419***	2.798	3.305***	1.999**	2.358*
	(0.600)	(0.670)	(1.716)	(0.648)	(0.486)	(0.647)	(1.914)	(0.677)	(0.825)	(1.207)
Regional NCL × Elasticity		-1.634***				-1.025***				-1.678***
		(0.288)				(0.187)				(0.435)
Sample	Full Sample	Elast. Sample	Low Elast.	High Elast.	Full Sample	Elast. Sample	Low Elast.	High Elast.	Full Sample	Elast. Sample
N	691	553	61	492	1902	706	62	644	2143	761
R-sq	0.083	0.472	0.465	0.214	0.263	0.348	0.568	0.228	0.117	0.222

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of least squares regressions at the county level, weighted by the county's population in 2002, relating the house price growth, the net worth growth, and the lending growth, net of the partial equilibrium effect of Table 2 column (1), to the regional and deposit network NCL variables. Columns (2), (6) and (10), add the regional NCL interacted with the housing supply elasticity and control for the housing supply elasticity. Columns (3)-(4) and (7)-(8) split the sample between counties with housing supply elasticity above and below 1, and control for the housing supply elasticity. The period considered is 2002-2005. Net worth growth was trimmed at the 5% level, and the deposit network NCL was winsorized at the 5% in the Net Worth and Lending panels because of the larger sample sizes in their main specifications of columns (5) and (9), and for consistency in the remaining ones. Robust standard errors are below the coefficients in parentheses.

Table 10: Lending Growth, 2002-2005

	(1)	(2)	(3)	(4)	(5)
Net Worth Growth	1.150***	1.008***	1.239***	1.302***	1.261***
	(0.256)	(0.328)	(0.274)	(0.274)	(0.277)
House Price Growth	0.892***	0.813***	0.871***	0.997***	0.815***
	(0.194)	(0.194)	(0.202)	(0.189)	(0.208)
			Instruments		
Dep. Network APO	YES		YES	YES	YES
Elasticity	YES	YES	YES	YES	YES
Regional APO		YES	YES	YES	YES
Pop. Growth			YES	YES	YES
Income Growth				YES	
HUD_{2003}					YES
Kleinbergen-Papp F	10.26	8.32	7.31	6.33	7.18
Hansen J (p-value)	0.06	0.15	0.01	0.02	0.01
N	474	499	474	474	474
R-sq	0.394	0.429	0.355	0.325	0.342

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table reports estimates of least squares regressions, weighted by the county's population in 2002, relating the county's loans growth, net of the PE estimate $0.090 * APL_{g,2004} \times OCC_{2003} - 0.075 * OCC_{2003} - 0.010 * APL_{g,2004}$, to the county's net worth growth and house price growth. All columns include the housing supply elasticity in the instrument list. Columns (1) and (3)-(5) add the deposit network APO, columns (2)-(5) add the regional APO, column (3) adds population growth, column (4) adds income growth, and column (5) adds the fraction of loans originated by lenders regulated by the Department of Housing and Urban Development (HUD) in 2003. All specifications also include $APL_{g,2004}$ and OCC_{2003}. The period considered is 2002-2005. House price growth and the deposit network APO were trimmed at the 5% level. Robust standard errors are below the coefficients in parentheses.

Table 11: House Prices, Net Worth, and Lending, 2000-2006

	$\log(\text{House Price})_{n,t}$		$\log(\text{Net Worth})_{n,t}$		$\log(\text{Loan amount})_{n,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit Network $\text{APO}_{n,t}$	0.018	0.089	1.421***	2.180***	0.360**	0.501**
	(0.126)	(0.148)	(0.427)	(0.685)	(0.143)	(0.213)
Regional $\text{APO}_{n,t}$	0.565**	1.635***	0.392	0.505	0.643***	1.348***
	(0.255)	(0.263)	(0.339)	(0.527)	(0.245)	(0.377)
$\text{Elasticity}_n \times \text{Regional APO}_{n,t}$		-0.453***		-0.059		-0.238***
		(0.066)		(0.041)		(0.052)
	Controls					
County FE, Year FE	YES	YES	YES	YES	YES	YES
APL, OCC, Post Controls	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Elast. Sample	Full Sample	Elast. Sample	Full Sample	Elast. Sample
N	4041	3275	9778	4186	9847	4206
R-sq	0.845	0.874	0.983	0.981	0.993	0.991

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of least squares regressions at the county level, weighted by the county's population in 2000, relating the change in the county's (log) house price level, (log) net worth, and the (log) amount of newly originated loans, net of the PE estimate $0.090 * APL_{g,t} \times Post_{2004} \times OCC_{2003} - 0.075 * Post_{2004} \times OCC_{2003} - 0.010 * APL_{g,t} \times OCC_{2003}$, to the regional and deposit network APO variables. All columns include county and year fixed effects, and control for $APL_{g,t}$, $APL_{g,t} \times Post_{2004}$, $OCC_{2003} \times Post_{2004}$, and $APL_{g,t} \times OCC_{2003}$. Columns (2), (4), and (6) add the interaction of the housing supply elasticity with the regional APO. The sample includes years from 2000 to 2006. The (log) house price level was trimmed at the 1% level, and the deposit network APO at the 5% level. Robust standard errors, clustered at the county level, are below the coefficients in parentheses.

Table 12: Lending Growth, 2002-2005

	(1)	(2)	(3)
NCL 2002	0.631**	0.652**	0.601*
	(0.310)	(0.306)	(0.322)
Regional NCL		1.970***	
		(0.517)	
Deposit Network NCL		2.216***	
		(0.704)	
Net Worth Growth			0.919***
			(0.225)
House Price Growth			0.517**
			(0.213)
	Instruments/Controls		
County FE	YES		
Regional NCL			YES
Elasticity			YES
Deposit Network NCL			YES
Kleinbergen-Papp F	-	-	637.86
Hansen J (p-value)	-	-	0.97
N	90457	84958	46706
R-sq	0.160	0.053	0.077

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table reports estimates of least square regressions, weighted by the lending share in the county interacted with the county's 2002 population, relating the lender's loans growth to their NCL as of 2002 in column (1) (OLS), and the regional and deposit network NCL in column (2) (OLS), and the county's net worth and house price growth in column (3) (2SLS). Column (1) includes county fixed effects. Column (3) uses the regional and deposit network NCLs, as well as the housing supply elasticity, as instruments. The period considered is 2002-2005. The deposit network NCL and net worth growth were winsorized and trimmed, respectively, at the 5% level. Robust standard errors, clustered at the bank holding company level, are below the coefficients in parentheses.

Table 13: Log of Loan Amount, 2000-2006

	(1)	(2)	(3)
$APL_{g,t} \times Post_{2004} \times OCC$	0.090***	0.103***	0.112***
	(0.025)	(0.028)	(0.035)
Deposit Network $\mathrm{APO}_{n,t}$		0.535***	
		(0.135)	
Regional $\mathrm{APO}_{n,t}$		0.557**	
		(0.244)	
log(Net Worth)$_{n,t}$			0.309***
			(0.095)
log(House Price)$_{n,t}$			1.054***
			(0.203)
	Instruments/Controls		
Cou.-Agency FE, Cou.-Year FE	YES		
Cou.-Agency FE, Year FE		YES	YES
APL, OCC, Post Controls	YES	YES	YES
Deposit Network $\mathrm{APO}_{n,t}$			YES
Regional $\mathrm{APO}_{n,t}$			YES
$\mathrm{Post}_{2004} \times \mathrm{OCC}_{2003}$		YES	YES
$\mathrm{APL}_{g,t} \times \mathrm{OCC}_{2003}$		YES	YES
Kleinbergen-Papp F	-	-	7.57
Hansen J (p-value)	-	-	0.25
N	118501	57595	24149
R-sq	0.985	0.980	-

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of least squares regressions, weighted by the county's population in 2000, relating the (log) amount of newly originated loans under each regulatory agency to $APL_{g,t} \times Post_{2004} \times OCC$. Column (2) adds the regional and deposit network APO, and column (3) instead adds the county's (log) net worth and (log) house price level. Columns (1) and (2) are OLS specifications, column (3) is a 2SLS specification. Column (1) includes county-agency fixed effects, and county-year fixed effects. Columns (2) and (3) include county-agency fixed effects and year fixed effects. Column (1) controls for $APL_{g,t} \times OCC$ (coefficient estimate -0.010, st. error 0.016), and $OCC \times Post_{2004}$ (coefficient estimate -0.075***, st. error 0.014). Columns (2) and (3) control for $APL_{g,t}$, $APL_{g,t} \times OCC$, $APL_{g,t} \times Post_{2004}$, and $OCC \times Post_{2004}$. The sample includes years from 2000 to 2006. The (log) house price level was trimmed at the 1% level, and the deposit network APO at the 5% level. Robust standard errors, clustered at the county level, are below the coefficients in parentheses.

Table 14: Network Misspecification

	β_{pe} = 0.630		β_{GM} = 2.903		FI Channel = 1.425		H Channel = 1.478		FI Share = 0.491		H Share = 0.509	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
N	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Correct network												
300	0.630	0.029	2.908	0.186	1.436	0.209	1.471	0.194	0.494	0.062	0.506	0.062
1000	0.630	0.015	2.907	0.095	1.430	0.105	1.477	0.103	0.492	0.032	0.508	0.032
2000	0.631	0.011	2.901	0.071	1.422	0.076	1.479	0.074	0.490	0.023	0.510	0.023
3000	0.630	0.009	2.900	0.056	1.425	0.067	1.476	0.065	0.491	0.021	0.509	0.021
Panel B: Correct links, incorrect weights												
300	0.630	0.028	2.900	0.187	1.429	0.210	1.470	0.194	0.492	0.062	0.506	0.062
1000	0.630	0.015	2.899	0.095	1.422	0.107	1.477	0.104	0.491	0.033	0.509	0.033
2000	0.631	0.011	2.893	0.071	1.413	0.076	1.480	0.074	0.488	0.023	0.512	0.023
3000	0.630	0.009	2.896	0.057	1.418	0.065	1.478	0.060	0.490	0.019	0.510	0.019
Panel C: Incorrect links (20%), incorrect weights												
300	0.630	0.028	3.129	0.234	1.658	0.297	1.470	0.211	0.528	0.073	0.472	0.073
1000	0.630	0.015	3.121	0.120	1.641	0.153	1.480	0.114	0.525	0.039	0.475	0.039
2000	0.631	0.011	3.116	0.089	1.637	0.111	1.479	0.081	0.525	0.027	0.475	0.027
3000	0.630	0.009	3.118	0.074	1.639	0.092	1.479	0.065	0.526	0.022	0.474	0.022

Table 15: Confounding the Credit Supply Shock

	β_{pe} = 0.630		β_{GM} = 2.903		FI Channel = 1.425		H Channel = 1.478		FI Share = 0.491		H Share = 0.509	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
N	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: No confounding shock												
300	0.628	0.029	2.900	0.105	1.420	0.081	1.480	0.068	0.490	0.018	0.510	0.018
1000	0.630	0.016	2.903	0.060	1.425	0.042	1.478	0.039	0.491	0.009	0.509	0.009
2000	0.630	0.011	2.902	0.043	1.425	0.0311	1.477	0.027	0.491	0.007	0.509	0.007
3000	0.630	0.009	2.903	0.033	1.425	0.025	1.478	0.021	0.491	0.006	0.509	0.006
Panel B: Confounding demand shock												
300	0.630	0.028	3.280	0.086	1.482	0.072	1.798	0.050	0.452	0.014	0.548	0.014
1000	0.630	0.015	3.284	0.048	1.488	0.038	1.796	0.028	0.453	0.007	0.547	0.007
2000	0.630	0.012	3.281	0.033	1.487	0.026	1.794	0.020	0.453	0.005	0.547	0.005
3000	0.630	0.009	3.283	0.028	1.487	0.022	1.796	0.017	0.453	0.004	0.547	0.004

Table 16: Lending Growth, 2002-2005

	(1)	(2)	(3)	(4)	(5)
Net Worth Growth	0.991***	0.710***	0.574***	1.593***	
	(0.201)	(0.189)	(0.129)	(0.231)	
House Price Growth	0.597***	1.068***	0.779***		1.166***
	(0.201)	(0.177)	(0.206)		(0.202)
	Instruments				
Net Worth Growth			YES		
House Price Growth		YES			
Reg. & Dep. network NCL	YES	YES	YES	YES	YES
Elast. & Reg. NCL $\times$ Elast.	YES	YES	YES	YES	YES
Kleinbergen-Papp F	23.36	26.56	26.75	45.53	34.21
Hansen J	3.35	11.68	13.16	13.53	38.20
Hansen J (p-value)	0.19	0.01	0.00	0.00	0.00
N	497	497	497	497	549
R-sq	0.459	0.545	0.524	0.163	0.548

The table reports estimates of 2SLS regressions, weighted by the county's population in 2002, relating the county's loans growth, net of the PE effect estimate of Table 2 column (1), to the county's net worth growth and house price growth. All columns include the regional and deposit network NCLs, as well as the housing supply elasticity along with its interaction with the regional NCL in the instrument list. Column (2) adds house price growth to the instrument list, and column (3) instead adds net worth growth. The period considered is 2002-2005. Net worth growth was trimmed at the 5% level. Robust standard errors are below the coefficients in parentheses.

Table 17: Log of Loan Amount, 2000-2006

	(1)	(2)	(3)	(4)	(5)
$\log(\text{Net Worth})_{n,t}$	0.236***	0.236***	0.039***	0.248**	
	(0.076)	(0.082)	(0.011)	(0.119)	
$\log(\text{House Price})_{n,t}$	1.311***	0.867***	1.314***		1.314***
	(0.179)	(0.060)	(0.184)		(0.187)
			Controls		
County FE, Year FE	YES	YES	YES	YES	YES
APL, OCC, Post Controls	YES	YES	YES	YES	YES
			Instruments		
Net Worth Growth			YES		
House Price Growth		YES			
Dep. Network APO	YES	YES	YES	YES	YES
Regional $\text{APO}_{n,t}$	YES	YES	YES	YES	YES
$\text{Post}_{2004} \times \text{OCC}_{2003}$	YES	YES	YES	YES	YES
$\text{APL}_{g,t} \times \text{OCC}_{2003}$	YES	YES	YES	YES	YES
Kleinbergen-Papp F	7.54	8.73	8.12	9.29	8.08
Hansen J (p-value)	0.37	0.01	0.02	0.00	0.01
N	4026	4026	4026	9778	4041
R-sq	0.100	0.172	0.228	-	0.223

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of least squares regressions, weighted by the county's population in 2000, relating the (log) amount of newly originated loans, net of the PE estimate $0.090 * APL_{g,t} \times Post_{2004} \times OCC_{2003} - 0.075 * Post_{2004} \times OCC_{2003} - 0.010 * APL_{g,t} \times OCC_{2003}$, to the county's (log) net worth (cols (1)-(4)) and (log) house price level (cols (1)-(3) and (5)). All columns include county and year fixed effects and control for $APL_{g,t}, APL_{g,t} \times Post_{2004}$. Column (2) adds the (log) house price level to the instrument list, and column (3) instead adds the (log) net worth. The sample includes years from 2000 to 2006. The (log) house price level was trimmed at the 1% level, and the deposit network APO at the 5% level. Robust standard errors, clustered at the county level, are below the coefficients in parentheses.

Table 18: Lending Growth, 2002-2005

	OLS		2SLS			
	(1)	(2)	(3)	(4)	(5)	(6)
NCL 2002	0.631**					
	(0.306)					
Net Worth Growth (loa)		0.590***	1.440***	1.450***	1.372***	1.095***
		(0.121)	(0.292)	(0.294)	(0.289)	(0.237)
House Price Growth		1.176***	0.605***	0.582***	0.603***	0.704***
		(0.154)	(0.184)	(0.194)	(0.196)	(0.194)
	Instruments/Controls					
County FE	YES					
Regional NCL			YES	YES	YES	YES
Deposit network NCL			YES	YES	YES	YES
Elasticity			YES	YES	YES	YES
Regional NCL × Elast.				YES	YES	YES
Regional elast. (dep)					YES	
Regional elast. (loa)						YES
Level	Lender	County	County	County	County	County
Kleinbergen-Papp F	-	-	23.09	22.06	19.83	17.84
Hansen J (p-value)	-	-	0.86	0.79	0.47	0.01
N	90457	620	496	496	496	496
R-sq	0.160	0.558	0.518	0.512	0.519	0.545

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table reports estimates of least square regressions, weighted by the county's population in 2002 (cols (2)-(6)) and the lending share in the county interacted with the county's 2002 population (col (1)). Column (1) relates the lender's loans growth to their NCL as of 2002. Columns (2)-(6) relate the county's loans growth, net of the PE effect estimate of column (1), to the county's net worth growth (weighted by mortgage loans) and house price growth. Column (1) includes county fixed effects. Columns (3)-(6) use the regional and deposit network NCLs, as well as the housing supply elasticity, as instruments. Column (4) adds the regional NCL interacted with the housing supply elasticity, column (5) further adds the deposit network elasticity, and column (6) instead adds the mortgage loan network elasticity. The period considered is 2002-2005. Net worth growth was trimmed at the 5% level. Robust standard errors, clustered at the county and bank holding company levels in column (1), are below the coefficients in parentheses.

Table 19: Local and Global Regional Multipliers, PLS surge

	Lending Growth	
	(1)	(2)
NCL 2002	2.142***	2.530***
	(0.482)	(0.362)
External dep. network NCL	1.263**	
	(0.642)	
N	2131	3081
R-sq	0.115	0.102

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of weighted least squares regressions at the county level, with weights equal to the population in 2002 of each county, relating the county's loans growth, net of the partial equilibrium effect of Table 2 column (1), to the county's 2002 NCL and the external deposit network NCL. The period considered is 2002-2005. Robust standard errors are below the coefficients in parentheses.

Table 20: Local and Global Regional Multipliers, States' APL laws

	(1)	(2)
Regional $\mathrm{APO}_{\mathrm{n,t}}$	0.643***	0.703***
	(0.245)	(0.246)
Deposit Network $\mathrm{APO}_{\mathrm{n,t}}$	0.360**	
	(0.143)	
	Controls	
County FE, Year FE	YES	YES
APL, OCC, Post Controls	YES	YES
N	9847	9847
R-sq	0.993	0.993

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The table presents coefficient estimates of least squares regressions at the county level, weighted by the county's population in 2000, relating the change in the county's (log) amount of newly originated loans, net of the PE estimate $0.090 * APL_{g,t} \times Post_{2004} \times OCC_{2003} - 0.075 * Post_{2004} \times OCC_{2003} - 0.010 * APL_{g,t} \times OCC_{2003}$, to the regional and deposit network APO variables. All columns include county and year fixed effects, and control for $APL_{g,t}, APL_{g,t} \times Post_{2004}, OCC_{2003} \times Post_{2004}$, and $APL_{g,t} \times OCC_{2003}$. The sample includes years from 2000 to 2006. The (log) house price level was trimmed at the 1% level, and the deposit network APO at the 5% level. Robust standard errors, clustered at the county level, are below the coefficients in parentheses.

B.4.3 Additional Figures

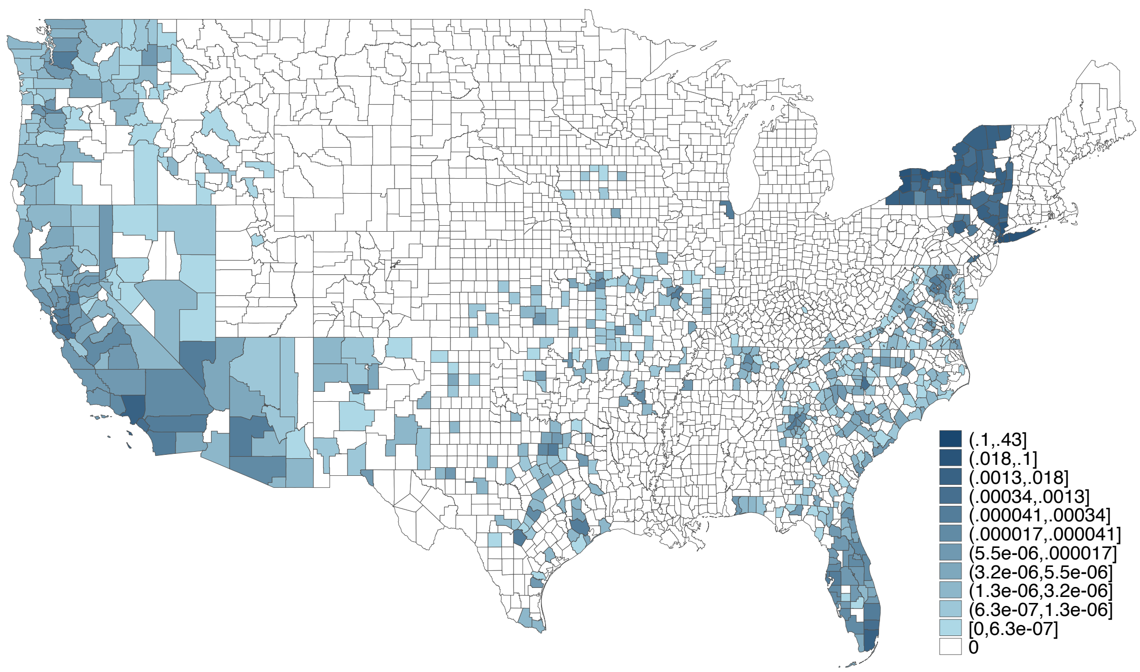
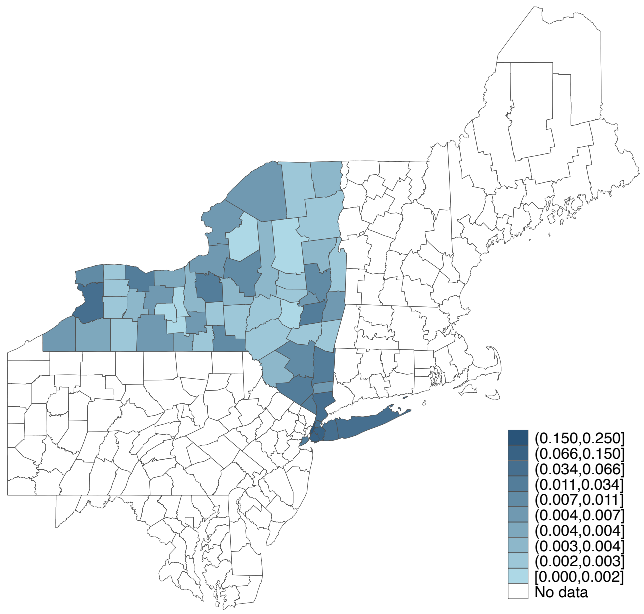
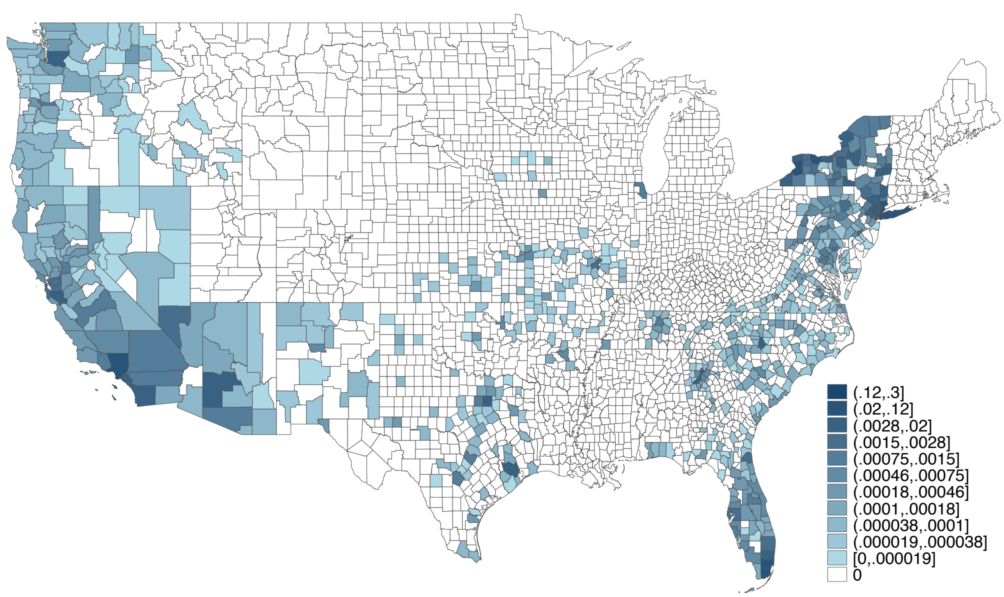


Figure 4: Weights in the deposit network APO of NY county.
The figure shows the heat maps of the weights in the deposit network APO of equation (19) for New York county.



(a) Regioanl NCL



(b) Deposit Network NCL

Figure 5: Weights in the regional NCL (panel a) and deposit network NCL (panel b) of NY county.
The figure shows the heat maps of the weights in the regional NCL (panel a) of equation (16) and the deposit network NCL (panel b) of equation (17) for New York county.