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Residential Concentration Dampens Monetary Policy Transmission

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This paper analyzes how the spatial structure of housing affects monetary policy transmission. I integrate spatial structure into a monetary business cycle model with housing. Spatial structure matters economically through households' location preferences and residential externalities. These two features are reflected in two measures of residential concentration. Higher residential concentration dampens consumption responses to interest rate changes through housing demand. In an empirical analysis, I create model-consistent measures of residential concentration for US and Eurozone regions, using geospatial data based on satellite imagery. I empirically validate the model's predictions in a state-dependent local projections framework. My paper identifies residential concentration as a fundamental determinant of monetary policy transmission.

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1 Introduction

Monetary policy is a central instrument for macroeconomic stabilization and a core focus of macroeconomic research (Ramey, 2016). A growing literature documents substantial geographic heterogeneity in monetary policy transmission (see, for example, Beraja et al., 2019; Aastveit and Anundsen, 2022). The role of housing is prevalent in this literature. Housing markets are geographically segmented and hence a natural source for geographic heterogeneity; especially given the importance of housing for monetary policy transmission (Iacoviello, 2005). However, this literature has so far overlooked the *spatial structure* of housing (that is, the distribution of housing across space), a key object of interest in spatial economics (Anas et al., 1998). The spatial structure of housing shapes local economic conditions, most importantly for this context, housing prices. This should matter for monetary policy transmission. Interest rate changes may, for instance, affect households differently in dense urban centers, characterized by high housing prices, than in rural areas. Therefore, this paper brings a spatial economic perspective to the study of monetary policy and asks: *Does the spatial structure of housing matter for monetary policy transmission?*

To address this question, first, I integrate spatial structure into a monetary business cycle model with housing. I describe two novel channels of monetary policy transmission that depend on the spatial structure of housing. Second, using geospatial data based on satellite imagery, I empirically validate the model's predictions.

Model. My model describes a region consisting of locations that differ in centrality and residential density. Households derive utility from consumption and housing service flows, where housing can be owned or rented. Owned housing is used as collateral for mortgage debt (following Iacoviello, 2005). The interest rate fluctuates over time.

The economic role of space is twofold. First, households prefer to live in central locations, obtaining higher utility from a given unit of housing (*location preferences,* dating back to Alonso, 1964). Second, households obtain local spillovers in housing service flows, reflecting local amenities, in addition to the housing service flows that they derive from the sizes of their homes (*residential externalities,* following Rossi-Hansberg et al., 2010). Higher residential density at a location implies stronger residential externalities.[1]

Mechanisms. In my model, the spatial structure of housing affects households' consumption responses to interest rate changes through location preferences and residential externalities.

[1] One might also consider negative amenities, such as noise or pollution. In line with the spatial economic literature, I assume that the *net* effect of density on amenities is positive (see, for example, Ahlfeldt et al., 2015).

First, consider location preferences. In central locations, a given unit of housing provides higher utility, which raises housing demand and hence prices. Now, assume the interest rate decreases, in response to which households increase their housing demand. In central locations, they must do so at higher prices. Balancing their utility between housing and consumption, households increase consumption less in response to the rate cut in a central location than in a peripheral location, all else equal – a dampening channel. The spatial structure of housing determines the *aggregate* strength of this channel: If a larger share of the model region's housing stock is located centrally, households increase their housing demand at higher prices on average. Hence, the dampening of monetary policy transmission to household consumption through location preferences is stronger.

Next, consider residential externalities. In a high-density location, residential externalities provide a large stream of housing service flows. Consequently, households can adjust their home sizes with relatively little effect on housing service flows. Households are therefore more inclined to smooth utility via their home sizes. Hence, when the interest rate decreases, households in a location with stronger externalities expand their home sizes more and increase consumption less, relative to households in a location with weaker externalities, all else equal. This constitutes a second dampening channel. Again, the spatial structure of housing determines the *aggregate* strength of this channel: If the average local residential density in the model region is higher, the dampening of monetary policy transmission to household consumption through residential externalities is stronger.

Quantitative model analysis. I calibrate the model using data from primarily the American Community Survey and the satellite-imagery-based Global Human Settlement Layer. I align multiple datasets from these two databases on a common spatial grid. From the combined information, I construct spatial data moments that reflect relative housing prices and household masses per unit of housing. I match these moments with my model in steady state, together with US national data moments. Using the calibrated model, I compare model regions that are identical in parameters and only differ in their spatial structures. I find that in a region with low average centrality and residential density, consumption rises by 0.54% in response to an unexpected 25-basis-point interest rate cut, whereas in a region with high average centrality and residential density, consumption rises by 0.37%. This corresponds to a dampening effect of $1 - (0.37\%/0.54\%) \approx 30\%$, which is comparable to the effects of other well-known factors influencing monetary policy transmission, such as maturity structure or the cyclicality of income risk (see Auclert et al., 2024).

I decompose the two channels by recalibrating the model with each channel being active individually. I find that location preferences alone generate a dampening effect of 20%, while for residential externalities this amounts to 5%. The two channels reinforce each other, such that the total effect with both channels being active amounts to 30%. The decomposition exercise also reveals that both spatial features are required for the model to match the US national and spatial data moments. Omitting either of the channels from the model leads to unrealistic statements about observable statistics.

Moreover, the model identifies high-density central locations as the main sources of dampening effects, as they are associated with strong location preferences *and* strong residential externalities. The pronounced dampening effect in high-density central locations is carried to other locations through region-wide goods and labor markets. I find such spatial linkages to be notable, but not essential for aggregate dampening effects, based on an alternative model version in which all markets are local. Intuitively, spatial linkages distribute a shock's impact within a region, while aggregate dampening effects are mostly determined by the prevalence of high-density central locations, as they host large populations.

Finally, I show that a model version without spatial structure and hence no location-specific features fails to reproduce the results of the baseline model. Intuitively, without distinguishing between the centrality of locations, it is impossible to generate the location preference channel. The residential externality channel is active, albeit incorrectly attributing a uniform level of externalities to all households.

Empirical analysis. In the empirical part of the paper, I quantify dampening effects without imposing the structural assumptions of my model. To this end, I use the Global Human Settlement Layer to conduct measurements on the spatial structures of regions in the United States and the Eurozone (for the latter, I do not have sufficient data to calibrate the model). I measure the share of a region's housing stock that is located centrally (residential *centralization*) and the average local residential density of a region (residential *clustering*). Residential *concentration* is the overarching concept for centralization and clustering (see Anas et al., 1998). Appendix A1 provides an overview of spatial terminology.

I use centralization and clustering as state variables in a state-dependent Jordà (2005) local projections framework. Exploiting cross-regional variation, this empirical strategy allows me to estimate effects of identified monetary policy shocks[2] as a function of centralization and clustering. I employ region fixed effects and control for features that are not represented in my model: sectoral composition, demographics, and unmodeled housing market characteristics. Note that I explicitly do not want to control for variables that are represented in my model.

The empirical results align with the quantitative model results and hold with data on annual consumption (US) as well as quarterly income (US) or GDP (Eurozone); different definitions of spatial measures and outcome variables; different shock directions, subsamples, and lag structures; and when removing groups of controls one at a time.

Policy implications. According to my results, residential concentration dampens consumption responses to interest rate changes, such that monetary interventions can generate systematically

[2] For the United States, I use shocks from Aruoba and Drechsel (2025) until 2008 and from Bügel et al. (2024) after 2008. For the Eurozone, I use shocks from Gulyas et al. (2024). In both cases, I take into account shadow rates for zero-lower-bound periods from Wu and Xia (2016) and Wu and Xia (2020) as lagged control variables. For robustness, I use shocks from Jarociński and Karadi (2020) for both the United States and the Eurozone.

uneven outcomes across space. This heterogeneity matters for both the assessment and the design of monetary policy.

First, accounting for this spatial heterogeneity can improve central banks' evaluation of responses to interest rate changes. The proposed empirical measures can be constructed for any geographical context across the globe and employed to predict effects of monetary policy across regions, specific parts of regions, or between urban and rural settings. Second, as urbanization patterns evolve over time, monitoring residential concentration can help anticipate shifts in monetary policy effectiveness.

Furthermore, fiscal or macroprudential policymakers could design spatially targeted policies that mitigate spatial differences in monetary policy transmission and strengthen consumption stabilization in high-concentration urban areas.

Relation to the macroeconomic literature. By demonstrating that the spatial structure of housing matters for monetary policy transmission, my paper primarily contributes to a growing macroeconomic literature that analyzes geographic heterogeneity in the effects of monetary policy (see, for example, Beraja et al., 2019; Aastveit and Anundsen, 2022; Corsetti et al., 2022; Albuquerque et al., 2024; de Groot et al., 2024; Hintermaier and Koeniger, 2024; Bellifemine et al., 2025; Favara et al., 2025; Herreño and Pedemonte, 2025).

Furthermore, my paper contributes to a rich macroeconomic literature that studies the role of housing markets in monetary policy transmission, with the seminal contribution being Iacoviello (2005). My model introduces two new channels into this literature, building on established spatial housing market characteristics. Established non-spatial housing market characteristics in this context are ownership composition (Cloyne et al., 2020; Hintermaier and Koeniger, 2024; Albuquerque et al., 2025), mortgage market structure (Di Maggio et al., 2017; Benetton et al., 2025; Hedlund et al., 2025), refinancing activity (Beraja et al., 2019; Chen et al., 2020; Di Maggio et al., 2020; Eichenbaum et al., 2022; Anenberg et al., 2025; Kinnerud, 2025), and housing construction elasticity (Aastveit and Anundsen, 2022; Albuquerque et al., 2024). Housing construction elasticity is closely related to residential concentration: More concentrated regions should face stronger constraints on housing construction. My model abstracts from the housing construction sector, while my empirical framework controls for housing construction elasticity. Note that even though the housing stock is constant in my model, housing *supply* is not.

Relation to the spatial economic literature. Spatial economic modeling, traditionally based on static frameworks, has recently been integrating dynamic elements. (for a literature review, see Desmet and Parro, 2025). Most papers that investigate dynamic spatial equilibrium focus on long time horizons. My model provides the first description of within-region spatial equilibrium effects over the short time horizon relevant for monetary policy transmission. The most closely related paper in this aspect is Bellifemine et al. (2025), characterizing a short-run equilibrium across regions without spatially granular housing market characteristics.

Lastly, my empirical analysis connects to a spatial economic literature concerned with measuring economically relevant features of spatial structure (for literature reviews, see Marcon and Puech, 2017; Duranton and Puga, 2020). In line with this literature, a naive density measure (total housing volume of a region divided by its total area) fails to capture empirical variation that reflects the economic channels in my setting.

Roadmap. The remainder of this paper is organized as follows. Sections 2 to 5 describe the structural analysis. Sections 6 to 8 describe the empirical analysis. Section 9 concludes.

2 A monetary business cycle model with spatial structure

Consider a region consisting of N locations, indexed by n. Housing V_n is measured in terms of volume, uniformly distributed within each location, and used for residential purposes. The area of each location is normalized to 1, such that a location's residential density is defined by its exogenous housing volume. Time, indexed by t, is discrete and measured in calendar quarters.

Households. There are two types of infinitely-lived households in every location: savers $\mathcal{S}$ and borrowers $\mathcal{B}$, following the standard Iacoviello (2005)-type framework. For any given household, its type and location is fixed. Borrowers are defined by having a lower discount factor than savers, such that they want to borrow from savers. Household type $\mathcal{T} \in \{\mathcal{S}, \mathcal{B}\}$ has a mass of $\mu_n^{\mathcal{T}} > 0$ per unit of V_n in location n, such that the mass of type-$\mathcal{T}$ households in location n is $M_n^{\mathcal{T}} = \mu_n^{\mathcal{T}} V_n$. In time period t, a household of type $\mathcal{T}$ in location n obtains utility

$$U_{t,n}^{\mathcal{T}} = \log\left(C_{t,n}^{\mathcal{T}}\right) + \omega_n \log\left(H_{t,n}^{\mathcal{T}}\right) - \left(L_{t,n}^{\mathcal{T}}\right)^{\delta} / \delta \quad \text{for} \quad \mathcal{T} \in \{\mathcal{S}, \mathcal{B}\} \tag{1}$$

from consumption $C_{t,n}^{\mathcal{T}}$, housing service flows $H_{t,n}^{\mathcal{T}}$, and labor hours $L_{t,n}^{\mathcal{T}}$. The labor supply disutility parameter $\delta > 1$ specifies convex disutility. The housing utility weight ω_n represents *location preferences*. I will calibrate this weight to be higher in more central locations. A given unit of housing service flows $H_{t,n}^{\mathcal{T}}$ provides households with a higher level of utility in such locations.

Households obtain housing service flows from occupied housing volumes and *residential externalities* X_n. The externalities generated in a location are proportional to residential density:

$$X_n = \xi V_n, \tag{2}$$

with $\xi \geq 0$. This parsimonious specification follows the original specification from Rossi-Hansberg et al. (2010), while abstracting from the influence of the locations' shapes' on the generated level of externalities, as well as spillovers between locations, for simplicity. Directly following Rossi-Hansberg et al. (2010), housing service flows for savers are given by:

$$H_{t,n}^{\mathcal{S}} = V_{t,n}^{\mathcal{S},\mathcal{O}} + X_n, \tag{3}$$

where $V_{t,n}^{\mathcal{S},\mathcal{O}}$ denotes owner-occupied housing volume. Borrowers may furthermore rent housing from savers and obtain housing service flows from both owner-occupied and rented housing volume.[3] In other words, a borrower household owns a part and rents a part of the housing volume it occupies. This assumption follows an extension of the Iacoviello (2005)-type framework introduced in Ortega et al. (2011). It should be interpreted as borrowers representing constrained households who, for some part of the population, rent and for some part own housing. The housing service flows of borrowers are given by:

$$H^{\mathcal{B}}_{t,n} = \left(\phi^{\mathcal{O}}(V^{\mathcal{B},\mathcal{O}}_{t,n})^{1-\eta} + \phi^{\mathcal{R}}(V^{\mathcal{B},\mathcal{R}}_{t,n})^{1-\eta}\right)^{1/(1-\eta)} + X_n, \tag{4}$$

where $1/\eta > 0$ is the elasticity of substitution between owner-occupied housing $V^{\mathcal{B},\mathcal{O}}_{t,n}$ and rented housing $V^{\mathcal{B},\mathcal{R}}_{t,n}$. The preference weights $\phi^{\mathcal{O}}$ and $\phi^{\mathcal{R}}$, both > 0, are normalized such that $\phi^{\mathcal{O}} = 1 - \phi^{\mathcal{R}}$. Households may borrow $B^{\mathcal{T}}_{t,n}$ via mortgages up to a fraction $\gamma \in (0,1)$ of their owner-occupied housing value, given a real per-unit housing purchase price $P_{t,n}$:

$$B^{\mathcal{T}}_{t,n} \leq \gamma P_{t,n} V^{\mathcal{T},\mathcal{O}}_{t,n} \text{ for } \mathcal{T} \in \{\mathcal{S},\mathcal{B}\}, \tag{5}$$

to be interpreted as a regulatory loan-to-value constraint. The key feature that categorizes borrowers as borrowers is a stronger discounting of utility over time compared to savers:

$$0 < \beta^{\mathcal{B}} < \beta^{\mathcal{S}} < 1, \tag{6}$$

where $\beta^{\mathcal{T}}$ is a type-specific discount factor. Being strictly more present-focused in their preferences than savers, borrowers always borrow up to the loan-to-value constraint from savers:

$$B^{\mathcal{B}}_{t,n} = \gamma P_{t,n} V^{\mathcal{B},\mathcal{O}}_{t,n}. \tag{7}$$

Accordingly, savers provide funds for borrowers in the form of negative borrowing $B^{\mathcal{S}}_{t,n} < 0$. I define financial assets $A^{\mathcal{S}}_{t,n}$ of savers as $A^{\mathcal{S}}_{t,n} = -B^{\mathcal{S}}_{t,n}$. The quarterly gross real interest rate R_{t-1} accrues on the financial assets with which savers enter a period. Note that I do not distinguish between the interest rate on financial assets and the mortgage rate in my model. The savers' budget constraint is:

$$\underbrace{C^{\mathcal{S}}_{t,n}}_{\text{Consumption}} + \underbrace{P_{t,n}\left(V^{\mathcal{S},\mathcal{O}}_{t,n} - V^{\mathcal{S},\mathcal{O}}_{t-1,n} + V^{\mathcal{S},\mathcal{R}}_{t,n} - V^{\mathcal{S},\mathcal{R}}_{t-1,n}\right)}_{\text{Net housing purchases}} + \underbrace{A^{\mathcal{S}}_{t,n}}_{\text{Savings}} = \underbrace{W^{\mathcal{S}}_t L^{\mathcal{S}}_{t,n}}_{\text{Labor income}} + \underbrace{Q_{t,n} V^{\mathcal{S},\mathcal{R}}_{t,n}}_{\text{Rental income}} + \underbrace{R_{t-1} A^{\mathcal{S}}_{t-1,n}}_{\text{Return on savings}}, \tag{8}$$

where the consumption good is the numeraire, labor earns a real per-unit wage rate $W^{\mathcal{T}}_t$, and rental housing volume $V^{\mathcal{S},\mathcal{R}}_{t,n}$ is rented out at real per-unit price $Q_{t,n}$. Net housing purchases consist

[3] As shown in Achou et al. (2024) in a Iacoviello (2005)-type framework with a continuum of discount factors, low-discount-factor types endogenously sort into renting from high-discount-factor types. For simplicity, I assume here directly that low-discount-factor types (borrowers) always rent from high-discount-factor types (savers).

of the end-of-period owned housing value $P_{t,n}(V_{t,n}^{\mathcal{S},\mathcal{O}} + V_{t,n}^{\mathcal{S},\mathcal{R}})$ minus the beginning-of-period owned housing value $P_{t,n}(V_{t-1,n}^{\mathcal{S},\mathcal{O}} + V_{t-1,n}^{\mathcal{S},\mathcal{R}})$. Analogously, the borrowers' budget constraint is:

$$\underbrace{C_{t,n}^{\mathcal{B}}}_{\text{Consumption}} + \underbrace{P_{t,n}\big((1-\gamma)V_{t,n}^{\mathcal{B},\mathcal{O}} - V_{t-1,n}^{\mathcal{B},\mathcal{O}}\big)}_{\text{Net housing purchases}} + \underbrace{R_{t-1}\gamma P_{t-1,n}V_{t-1,n}^{\mathcal{B},\mathcal{O}}}_{\text{Mortgage debt payments}} + \underbrace{Q_{t,n}V_{t,n}^{\mathcal{B},\mathcal{R}}}_{\text{Rental expenditure}} = \underbrace{W_t^{\mathcal{B}}L_{t,n}^{\mathcal{B}}}_{\text{Labor income}}, \tag{9}$$

where mortgage debt $\gamma P_{t,n}V_{t,n}^{\mathcal{B},\mathcal{O}}$ is repaid next period with interest. Hence, mortgages can be interpreted as either being refinanced every period or having a variable interest rate. This assumption is standard in Iacoviello (2005)-type models and serves for tractability. In the model, a change in the interest rate immediately affects all borrowers. In reality, such a change only affects mortgage originators, refinancers, or adjustable-rate mortgage holders. Most mortgage holders in the United States (to which I will calibrate the model) hold fixed-rate mortgages and are hence not immediately affected; however, mortgage refinancing is quite prevalent in the United States (see, for example, Amromin et al., 2020).

I am now ready to describe households' optimal behavior. Formal derivations are provided in Appendix A2. Given housing purchase prices, rental prices, wage rates, and the interest rate, households in a given time period t and location n maximize their expected discounted sum of utility (1) by choosing consumption, housing volumes, and labor hours, subject to their budget constraint (8) or (9). Savers also choose the quantity of financial assets to save in, subject to the transversality condition

$$\lim_{k\to\infty} \mathbb{E}_t\Big[\big(C_{t+k,n}^{\mathcal{S}}\big)^{-1}A_{t+k,n}^{\mathcal{S}}\Big] = 0, \tag{10}$$

where $\mathbb{E}_t[\cdot]$ is the expectation operator. I obtain that, first, savers intertemporally substitute via an *Euler equation:*

$$\underbrace{\big(C_{t,n}^{\mathcal{S}}\big)^{-1}}_{\text{Marginal utility of current consumption}} = \underbrace{\beta^{\mathcal{S}}R_t\mathbb{E}_t\Big[\big(C_{t+1,n}^{\mathcal{S}}\big)^{-1}\Big]}_{\text{Discounted marginal utility of future consumption}}. \tag{11}$$

A similar optimality condition as the Euler equation arises from savers' intertemporal housing choices. Savers can purchase housing at per-unit price $P_{t,n}$, which they evaluate in terms of the marginal utility of consumption U_C. They balance this marginal cost with the marginal benefit of obtaining additional housing utility and being able to resell next period at $P_{t+1,n}$. This results in a first-order condition for *savers' owner-occupied housing demand:*

$$\underbrace{P_{t,n}\big(C_{t,n}^{\mathcal{S}}\big)^{-1}}_{\text{Per-unit purchase price in terms of } U_C} = \underbrace{\omega_n\big(H_{t,n}^{\mathcal{S}}\big)^{-1}}_{\text{Marginal utility of housing}} + \underbrace{\beta^{\mathcal{S}}\mathbb{E}_t\Big[P_{t+1,n}\big(C_{t+1,n}^{\mathcal{S}}\big)^{-1}\Big]}_{\text{Discounted per-unit resale price in terms of } U_C}. \tag{12}$$

An analogous optimality condition applies for borrowers. The marginal cost of owner-occupied housing consists of the per-unit down payment $(1-\gamma)P_{t,n}$, evaluated in terms of current U_C; as well as the repayment of per-unit mortgage debt $\gamma P_{t,n}$, evaluated in terms of next-period's discounted U_C. The first-order condition for *borrowers' owner-occupied housing demand* is therefore:

$$\underbrace{(1-\gamma)P_{t,n}\left(C^{\mathcal{B}}_{t,n}\right)^{-1}}_{\text{Per-unit down payment in terms of } U_C} + \underbrace{\beta^{\mathcal{B}} R_t \gamma P_{t,n} \mathbb{E}_t\left[\left(C^{\mathcal{B}}_{t+1,n}\right)^{-1}\right]}_{\text{Discounted per-unit mortgage debt payment in terms of } U_C}$$
$$= \underbrace{\omega_n \phi^{\mathcal{O}}\left(H^{\mathcal{B}}_{t,n}\right)^{-1}\left(V^{\mathcal{B},\mathcal{O}}_{t,n}/V^{\mathcal{B}}_{t,n}\right)^{-\eta}}_{\text{Marginal utility of owner-occupied housing}} + \underbrace{\beta^{\mathcal{B}}\mathbb{E}_t\left[P_{t+1,n}\left(C^{\mathcal{B}}_{t+1,n}\right)^{-1}\right]}_{\text{Discounted per-unit resale price in terms of } U_C}, \tag{13}$$

denoting $V^{\mathcal{B}}_{t,n} = \left(\phi^{\mathcal{O}}(V^{\mathcal{B},\mathcal{O}}_{t,n})^{1-\eta} + \phi^{\mathcal{R}}(V^{\mathcal{B},\mathcal{R}}_{t,n})^{1-\eta}\right)^{1/(1-\eta)}$. Next, consider the choices regarding rental housing. Savers can purchase a unit of housing at $P_{t,n}$, which constitutes a marginal cost, to rent it out at $Q_{t,n}$, which constitutes a marginal benefit. In the next period, they can resell this unit of housing. These considerations imply a first-order condition for *rental housing supply:*

$$\underbrace{P_{t,n}\left(C^{\mathcal{S}}_{t,n}\right)^{-1}}_{\text{Per-unit purchase price in terms of } U_C} = \underbrace{Q_{t,n}\left(C^{\mathcal{S}}_{t,n}\right)^{-1}}_{\text{Per-unit rental price in terms of } U_C} + \underbrace{\beta^{\mathcal{S}}\mathbb{E}_t\left[P_{t+1,n}\left(C^{\mathcal{S}}_{t+1,n}\right)^{-1}\right]}_{\text{Discounted per-unit resale price in terms of } U_C}. \tag{14}$$

Borrowers can rent housing from savers at $Q_{t,n}$ and obtain utility from rented housing, which implies a first-order condition for *rental housing demand:*

$$\underbrace{Q_{t,n}\left(C^{\mathcal{B}}_{t,n}\right)^{-1}}_{\text{Per-unit rental price in terms of } U_C} = \underbrace{\omega_n \phi^{\mathcal{R}}\left(H^{\mathcal{B}}_{t,n}\right)^{-1}\left(V^{\mathcal{B},\mathcal{R}}_{t,n}/V^{\mathcal{B}}_{t,n}\right)^{-\eta}}_{\text{Marginal utility of rented housing}}. \tag{15}$$

The only remaining choice variable is labor hours. Households balance the costs and benefits of working via standard *labor supply* first-order conditions:

$$\underbrace{\left(L^{\mathcal{T}}_{t,n}\right)^{\delta-1}}_{\text{Marginal disutility of labor}} = \underbrace{W^{\mathcal{T}}_t\left(C^{\mathcal{T}}_{t,n}\right)^{-1}}_{\text{Wage rate in terms of } U_C} \quad \text{for } \mathcal{T} \in \{\mathcal{S},\mathcal{B}\}. \tag{16}$$

Production. A regionally[4] representative firm $\mathcal{F}$ produces consumption goods Y_t using labor inputs $L^{\mathcal{S},\mathcal{F}}_t$ and $L^{\mathcal{B},\mathcal{F}}_t$, with labor input weights $\alpha^{\mathcal{T}} > 0$ for $\mathcal{T} \in \{\mathcal{S},\mathcal{B}\}$:

$$Y_t = \left(L^{\mathcal{S},\mathcal{F}}_t\right)^{\alpha^{\mathcal{S}}}\left(L^{\mathcal{B},\mathcal{F}}_t\right)^{\alpha^{\mathcal{B}}}. \tag{17}$$

The labor input weights are normalized such that $\alpha^{\mathcal{S}} = 1 - \alpha^{\mathcal{B}}$. Note that this functional form is standard in Iacoviello (2005)-type models and also used in similar models without housing (see,

[4]The assumption of a regional firm is not essential for the model results, as I show with an alternative model setup with location-specific firms in Section 5.3.

for example, Boehnert et al., 2025). The firm maximizes profits

$$Y_t - \left(W_t^{\mathcal{S}} L_t^{\mathcal{S},\mathcal{F}} + W_t^{\mathcal{B}} L_t^{\mathcal{B},\mathcal{F}}\right) \tag{18}$$

in a static optimization problem by choosing $L_t^{\mathcal{S},\mathcal{F}}$ and $L_t^{\mathcal{B},\mathcal{F}}$, given wage rates $W_t^{\mathcal{S}}$ and $W_t^{\mathcal{B}}$, with equilibrium profits being zero due to constant returns to scale. Its *labor demand* first-order conditions are:

$$\underbrace{\alpha^{\mathcal{T}}\left(Y_t / L_t^{\mathcal{T},\mathcal{F}}\right)}_{\text{Marginal productivity of labor}} = \underbrace{W_t^{\mathcal{T}}}_{\text{Marginal cost of labor}} \quad \text{for } \mathcal{T} \in \{\mathcal{S},\mathcal{B}\}. \tag{19}$$

Monetary policy. The quarterly gross real interest rate R_t is set by the monetary authority of the currency area in which the model region is located, and the model region is small relative to the currency area. Hence, the real interest rate is exogenous.[5] It is specified by:

$$R_t = R \exp\left(D_t\right), \tag{20}$$

where R is the steady-state interest rate and D_t is a stochastic log-deviation of the interest rate from its steady-state value. This deviation evolves as:

$$D_t = \rho D_{t-1} + E_t \tag{21}$$

with persistence $\rho \in (0,1)$, monetary policy shocks

$$E_t \overset{\text{i.i.d.}}{\sim} \mathcal{N}\left(0,\sigma^2\right), \tag{22}$$

and standard deviation of the shocks $\sigma > 0$. Expectations about the time path of interest rates are rational in the sense that

$$\left\{\mathbb{E}_t\left[E_{t+k}\right] = 0\right\}_{k=1}^{\infty}. \tag{23}$$

Market clearing. Representing the local nature of housing markets, each location is assigned its own housing and rental market clearing condition. The consumption goods market and the labor market clear at the regional level. The financial market does not have to clear at the regional level, consistent with the interest rate being exogenous to the model region.

Note that the regional market clearing conditions for consumption goods and labor give rise to spatial equilibrium linkages. Demand for consumption goods in one location affects labor demand and wages, and hence labor income, in all locations. Moreover, note that since labor

[5] This assumption serves for tractability. An earlier version of this paper used an endogenously set nominal interest rate with a Taylor rule, which delivered the same relevant model results.

markets clear at the regional level, commuting between locations is possible without restrictions. This loosens the conceptualization of households being tied to their locations.

Taking into account household masses, the market clearing conditions are given by

$$\underbrace{\mu_n^{\mathcal{S}} V_n V_{t,n}^{\mathcal{S},\mathcal{O}} + \mu_n^{\mathcal{B}} V_n V_{t,n}^{\mathcal{B},\mathcal{O}} + \mu_n^{\mathcal{B}} V_n V_{t,n}^{\mathcal{B},\mathcal{R}}}_{\text{Occupied housing volume}} = \underbrace{V_n}_{\text{Existing housing volume}} \quad \text{for } n = 1, ..., N, \tag{24}$$

$$\underbrace{\mu_n^{\mathcal{B}} V_n V_{t,n}^{\mathcal{B},\mathcal{R}}}_{\text{Rental volume demand}} = \underbrace{\mu_n^{\mathcal{S}} V_n V_{t,n}^{\mathcal{S},\mathcal{R}}}_{\text{Rental volume supply}} \quad \text{for } n = 1, ..., N, \tag{25}$$

$$\underbrace{\sum_{n=1}^{N} \mu_n^{\mathcal{S}} V_n C_{t,n}^{\mathcal{S}} + \sum_{n=1}^{N} \mu_n^{\mathcal{B}} V_n C_{t,n}^{\mathcal{B}}}_{\text{Consumption goods demand}} = \underbrace{Y_t,}_{\text{Production}} \tag{26}$$

$$\underbrace{L_t^{\mathcal{T},\mathcal{F}}}_{\text{Labor hours demand}} = \underbrace{\sum_{n=1}^{N} \mu_n^{\mathcal{T}} V_n L_{t,n}^{\mathcal{T}}}_{\text{Labor hours supply}} \quad \text{for } \mathcal{T} \in \{\mathcal{S},\mathcal{B}\}. \tag{27}$$

Equilibrium. I define a *rational-expectations dynamic spatial equilibrium* as quantities and prices

$$\Big\{ \big\{ \{C_{t,n}^{\mathcal{T}}\}_{\mathcal{T}\in\{\mathcal{S},\mathcal{B}\}} \big\}_{n=1}^{N}, \big\{ \{V_{t,n}^{\mathcal{T},\mathcal{O}}\}_{\mathcal{T}\in\{\mathcal{S},\mathcal{B}\}} \big\}_{n=1}^{N}, \big\{ \{V_{t,n}^{\mathcal{T},\mathcal{R}}\}_{\mathcal{T}\in\{\mathcal{S},\mathcal{B}\}} \big\}_{n=1}^{N}, \{A_{t,n}^{\mathcal{S}}\}_{n=1}^{N},$$
$$\big\{ \{L_{t,n}^{\mathcal{T}}\}_{\mathcal{T}\in\{\mathcal{S},\mathcal{B}\}} \big\}_{n=1}^{N}, \{L_t^{\mathcal{T},\mathcal{F}}\}_{\mathcal{T}\in\{\mathcal{S},\mathcal{B}\}}, Y_t, \{P_{t,n}\}_{n=1}^{N}, \{Q_{t,n}\}_{n=1}^{N}, \{W_t^{\mathcal{T}}\}_{\mathcal{T}\in\{\mathcal{S},\mathcal{B}\}} \Big\}_{t=0}^{\infty}$$

given: housing volumes $\{V_n\}_{n=1}^{N}$ which imply residential externalities $\{X_n\}_{n=1}^{N}$ as specified in (2), a sequence of real interest rates $\{R_t\}_{t=0}^{\infty}$ which evolves according to (20) and (21), with rational expectations about monetary policy shocks (22) as specified in (23), and parameters

$$\Big\{ \alpha^{\mathcal{S}}, \alpha^{\mathcal{B}}, \beta^{\mathcal{S}}, \beta^{\mathcal{B}}, \gamma, \delta, \eta, \{\mu_n^{\mathcal{S}}\}_{n=1}^{N}, \{\mu_n^{\mathcal{B}}\}_{n=1}^{N}, \xi, \rho, \sigma, \phi^{\mathcal{O}}, \phi^{\mathcal{R}}, \{\omega_n\}_{n=1}^{N} \Big\}$$

such that households optimize according to (1)-(16), the representative firm optimizes according to (17)-(19), and markets clear according to (24)-(27). A log-linearization, documented in Appendix A3, allows me to solve for the equilibrium in the context of the quantitative model analysis using standard methods relying on a generalized Schur decomposition. I obtain steady-state values of the model's variables by running a Levenberg-Marquardt optimization routine on the equilibrium conditions evaluated at steady state.

Before going into the quantitative model analysis, I discuss the model mechanisms. To this end, I employ equations from the log-linearized model and describe relationships that characterize the economic role of spatial structure.

3 How does spatial structure matter for monetary policy?

To prepare my discussion of the model mechanisms, I first describe the general effects of an unexpected interest rate *decrease*. In response to this shock, all households increase their consumption: Savers intertemporally substitute via their Euler equations, while borrowers respond in their consumption to changes in disposable income, being at their borrowing constraints. Their disposable income increases due to a decrease in mortgage debt service costs and an increase in labor income, which stems from increased consumption goods demand. Note that since borrowers are constrained, they have high marginal propensities to consume, which makes their consumption responses to interest rate changes essential for aggregate consumption responses. I will therefore focus on *borrowers' consumption responses* in the following.

Moreover, as the mortgage rate decreases, borrowers want to purchase housing: Borrowers derive high value from owner-occupied housing, since they use it as collateral. Savers sell housing to borrowers, experiencing wealth gains from demand-driven higher housing purchase prices. The response of rented housing demand is ambiguous. On the one hand, rental housing demand increases due to borrowers' increased disposable income. On the other hand, a lower interest rate induces borrowers to switch from rented housing to owner-occupied housing.

Channel 1: Location preferences. For the location preference channel, the key insight is that in more central, high-price locations, households must spend more to increase their occupied housing volumes following a rate cut, which crowds out some of the potential increase in consumption.

To reflect location preferences, I will calibrate the housing utility weight ω_n to be higher in central locations, which drives up steady-state housing purchase and rental prices P_n and Q_n in these locations. In locations with higher steady-state prices, any given expansion of housing requires a larger expenditure, leaving less room for consumption to increase. Specifically, observe how P_n and Q_n affect the borrowers' log-linearized budget constraint:

$$
\begin{aligned}
&C_n^{\mathcal{B}}\widehat{C}_{t,n}^{\mathcal{B}} + P_n V_n^{\mathcal{B},\mathcal{O}}\big((1-\gamma)\widehat{V}_{t,n}^{\mathcal{B},\mathcal{O}} - \widehat{V}_{t-1,n}^{\mathcal{B},\mathcal{O}} - \gamma\,\widehat{P}_{t,n}\big) + R\,\gamma\,P_n V_n^{\mathcal{B},\mathcal{O}}\big(\widehat{R}_{t-1} + \widehat{P}_{t-1,n} + \widehat{V}_{t-1,n}^{\mathcal{B},\mathcal{O}}\big)\\
&\quad + Q_n V_n^{\mathcal{B},\mathcal{R}}\big(\widehat{Q}_{t,n} + \widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}}\big) = W^{\mathcal{B}} L_n^{\mathcal{B}}\big(\widehat{W}_t^{\mathcal{B}} + \widehat{L}_{t,n}^{\mathcal{B}}\big),
\end{aligned}
\tag{28}
$$

where hats denote percentage deviations from steady state. In a high-ω_n location, it is more costly to purchase or rent more housing, that is, increase $\widehat{V}_{t,n}^{\mathcal{B},\mathcal{O}}$ or $\widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}}$ – which, however, borrowers want to do when the interest rate decreases (for rentals, this effect depends on the calibration). Balancing their utility from housing service flows and consumption via their housing demand first-order conditions (13) and (15), borrowers then dampen their consumption responses $\widehat{C}_{t,n}^{\mathcal{B}}$ as well as their housing demand responses $\widehat{V}_{t,n}^{\mathcal{B},\mathcal{O}}$ and $\widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}}$ (a negative rental housing demand responses becomes more negative), relative to households in a low-ω_n location.

One might object here that higher housing prices in more central locations amplify, rather than dampen, consumption responses: Higher housing prices imply higher steady-state mortgage debt, provided that they do not put too much downward pressure on the steady-state owner-occupied housing demand of borrowers. Interest rate changes thus have a stronger direct influence on borrowers' disposable income via mortgage debt service costs. However, a simple calculation shows this effect to be minor. Consider again the borrowers' log-linearized budget constraint, setting all variables that are irrelevant for this argument to zero:

$$\widehat{C}^{\mathcal{B}}_{t,n} = -R\gamma\widehat{R}_{t-1}\big(P_n V_n^{\mathcal{B},\mathcal{O}}/C_n^{\mathcal{B}}\big). \tag{29}$$

For illustration, I compare two locations, 1 and 2, where location 1 has the higher housing price. The difference in borrowers' consumption responses between the two locations is

$$\widehat{C}^{\mathcal{B}}_{t,1} - \widehat{C}^{\mathcal{B}}_{t,2} = -R\gamma\widehat{R}_{t-1}\underbrace{\big(P_1 V_1^{\mathcal{B},\mathcal{O}}/C_1^{\mathcal{B}} - P_2 V_2^{\mathcal{B},\mathcal{O}}/C_2^{\mathcal{B}}\big).}_{\text{Difference in } \mathcal{B}\text{'s housing-wealth-to-consumption ratio}} \tag{30}$$

I take the difference rather than the relative deviation here because the background variables that I set to zero will not actually be equal to zero in a model simulation, leading such a calculation to display misleading results when dividing the equations of two locations by each other. For illustration, I plug in standard values for the steady-state quarterly gross real interest rate R of 1.0075 (which corresponds to an annualized net real interest rate of 3%) and for the mortgage loan-to-value ratio limit γ of 90%, as well as an interest rate change $\widehat{R}_{t-1}$ of -6.25 basis points (hence an annualized change of 25 basis points). The difference in consumption responses is then merely $-1.0075 \times 0.90 \times (-0.000625) \approx 0.06\%$ times the difference in borrowers' housing-wealth-to-consumption ratio between the two locations. The debt service term is only able to generate small consumption response differences on its own.

A second potential objection is that spatial differences in housing price responses could drive spatial differences in consumption responses. Consider again the borrowers' log-linearized budget constraint with all variables that are irrelevant for this argument set to zero and $R \approx 1$ for illustrative purposes:

$$\widehat{C}^{\mathcal{B}}_{t,n} \approx \gamma\left(P_n V_n^{\mathcal{B},\mathcal{O}}/C_n^{\mathcal{B}}\right)\big(\underbrace{(\widehat{P}_{t,n} - \widehat{P}_{t-1,n})}_{\text{Difference in housing price responses over time}} - \widehat{R}_{t-1}\big). \tag{31}$$

Due to mortgage debt payments, the previous period's housing price response enters the calculation. If housing prices are higher in the current period, this allows for more mortgage borrowing, boosting borrowers' consumption (all else equal, most importantly, housing volumes). However, these higher prices also carry over to higher mortgage debt payments in the next period. A net effect from housing price responses on consumption responses can only occur via differences in housing price responses over time. This can, practically speaking, not become large enough to drive my results, as in the case of the debt service term. I abstract here from rental housing price responses, for which I discuss intuitions in Appendix A4.

Having potential objections addressed, I would like to shift the focus to how location preferences matter at a spatially aggregated level (rather than the level of individual locations). The average utility from a given unit of housing is reflected in the share of housing volume in high-ω_n locations, that is, central locations $\mathcal{C}$. I define this share as *residential centralization:*

$$\text{Residential centralization} = \frac{\sum_{n:n\in\mathcal{C}} V_n}{\sum_n V_n}. \tag{32}$$

If residential centralization is higher, a larger share of borrowers face high housing and rental prices and consequently dampen their consumption responses to interest rate changes.

Centralization reflects the price-level effect driven by location preferences. Strictly speaking, the associated consumption responses depend on the spatial distribution of borrower masses per unit of housing. I abstract from this aspect here, as well as in the discussion of the second channel, for expositional ease and in order to be able to bring the summary measures that I construct during the discussions directly to the data in the empirical part of the paper. For the quantitative model results, the definitions of these summary measures will be irrelevant.

Channel 2: Residential externalities. Stronger residential externalities also dampen the transmission of interest rate changes to household consumption. For the residential externality channel, the intuition is that stronger externalities render households' utility from housing service flows less sensitive to changes in home size. This makes households more inclined to smooth utility via their home sizes, such that they adjust their home sizes more and their consumption less in response to interest rate changes.

Consider the log-linearized first-order condition for savers' owner-occupied housing demand

$$\widehat{P}_{t,n} - \widehat{C}^{\mathcal{S}}_{t,n} = -\left(1-\beta^{\mathcal{S}}\right)\left(V_n^{\mathcal{S},\mathcal{O}}/H_n^{\mathcal{S}}\right)\widehat{V}_{t,n}^{\mathcal{S},\mathcal{O}} + \beta^{\mathcal{S}}\mathbb{E}_t\left[\widehat{P}_{t+1,n} - \widehat{C}^{\mathcal{S}}_{t+1,n}\right]. \tag{33}$$

The relevant conditions for borrowers are heavier in notation (see Appendix A2), which is why I choose to display the one of savers for exposition. The argument will again refer to borrowers.

Notice that a smaller steady-state ratio of housing service flows from occupied housing volume $V_n^{\mathcal{S},\mathcal{O}}$ to total housing service flows $H_n^{\mathcal{S}} = V_n^{\mathcal{S},\mathcal{O}} + X_n$ implies larger occupied housing volume responses $\widehat{V}_{t,n}^{\mathcal{S},\mathcal{O}}$. With stronger externalities, the curvature of savers' utility with respect to housing volume is reduced, implying a lower steady-state Arrow-Pratt measure of relative risk aversion over housing volume:

$$-V_n^{\mathcal{S},\mathcal{O}}\,\frac{\partial^2 U_n^{\mathcal{S}}/\partial\left(V_n^{\mathcal{S},\mathcal{O}}\right)^2}{\partial U_n^{\mathcal{S}}/\partial V_n^{\mathcal{S},\mathcal{O}}} = -V_n^{\mathcal{S},\mathcal{O}}\,\frac{-\omega_n/\left(V_n^{\mathcal{S},\mathcal{O}}+X_n\right)^2}{\omega_n/\left(V_n^{\mathcal{S},\mathcal{O}}+X_n\right)} = V_n^{\mathcal{S},\mathcal{O}}/H_n^{\mathcal{S}}, \tag{34}$$

which holds analogously for borrowers. Correspondingly, households in a higher-externality location, and especially borrowers who are the focus of this discussion due to their high marginal propensities to consume, amplify their adjustments in housing volume and, as the counterpart, dampen their adjustments in consumption in response to interest rate changes (relative to borrowers in a lower-externality location). Intuitively, following an interest rate change that calls for some form of economic adjustment, borrowers in a higher-externality location are more inclined to make this adjustment in terms of occupied housing volumes.

To describe the aggregate strength of this channel, I define the regional average level of residential externalities as

$$\bar{X} = \frac{\sum_{n=1}^{N} V_n \times X_n}{\sum_{n=1}^{N} V_n} = \xi \times \frac{\sum_{n=1}^{N} (V_n)^2}{\sum_{n=1}^{N} V_n}. \tag{35}$$

The convexity obtained through the squared terms reflects that a high-density location features strong externalities while also containing a large part of the regional population. Next, I define

$$\text{Residential clustering} = \bar{X} / \xi = \frac{\sum_{n=1}^{N} (V_n)^2}{\sum_{n=1}^{N} V_n} \tag{36}$$

to get an expression without ξ, such that residential clustering is an empirically observable object. If clustering in a region is higher, borrowers benefit from stronger externalities on average (given $\xi > 0$) and consequently dampen their consumption responses to interest rate changes more strongly. Clustering reflects local spillover effects from residential externalities.

A potential objection is that I do not model housing construction responses, even though this channel relies on the strength of housing demand responses, which might also invoke housing construction responses. Housing construction is indeed an important component of monetary policy transmission (see, for example, Iacoviello and Neri, 2010). If anything, it should be more difficult to build in a more clustered region, which would imply further dampening through housing construction and hence output responses, therefore also income responses and consumption responses. This interferes with a housing construction elasticity channel, which is not the focus of my paper. I control for housing construction elasticity in the empirical analysis.

Synthesis. Both channels imply dampened consumption responses to interest rate changes. The strength of the first channel is reflected in residential centralization, while the strength of the second channel is reflected in residential clustering. The overarching concept is *residential concentration* (see Anas et al., 1998). Hence, I conclude that higher residential concentration dampens the transmission of interest rate changes to household consumption.

Furthermore, the two channels reinforce each other if the characteristics "central" and "high-density" coincide for a location. In that case, borrowers are more willing to adjust their occupied housing volumes, while purchases or rentals happen at higher prices. Consumption responses are then dampened by more than with each channel individually.

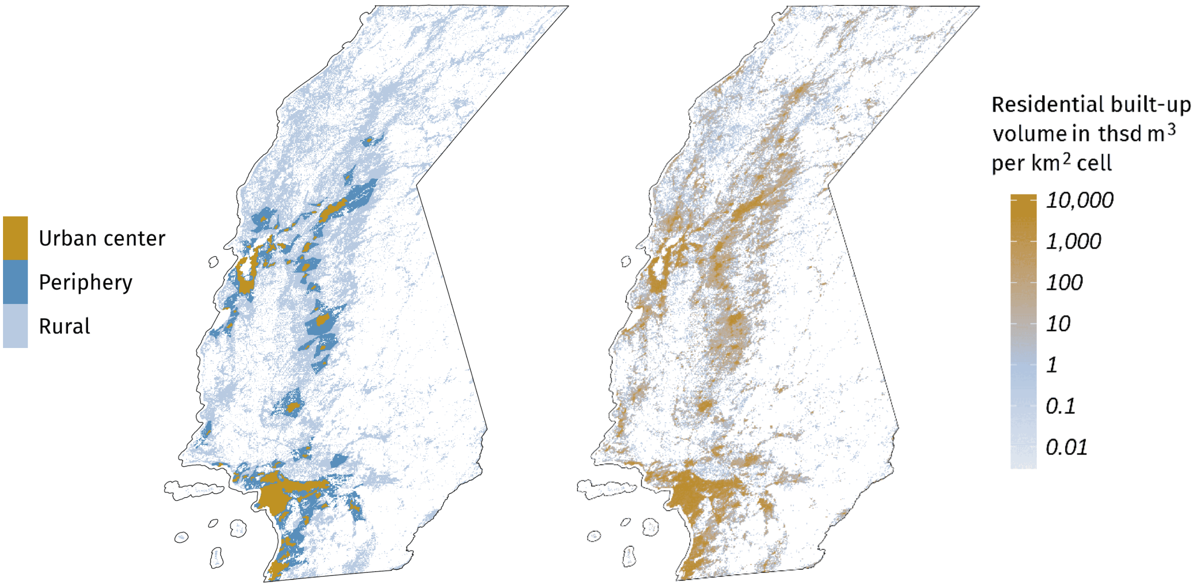
Note that the previous statement does not follow immediately and is based on observations from the quantitative analysis. First, the location preference channel dampens borrowers' housing demand responses, while the residential externality channel amplifies them. The net effect depends on the calibration. Quantitatively, the effect of residential externalities on housing demand responses easily dominates the effect of location preferences. Second, residential externalities put downward pressure on steady-state housing demand and hence prices due to free-riding behavior: Households can live in relatively small housing units while obtaining reasonable housing service flows. If this downward pressure is stronger than the upward pressure due to location preferences, the first dampening channel is shut down by externalities, as steady-state housing prices are not actually higher in central locations. Quantitatively, the price-increasing effect of location preferences easily dominates the price-decreasing effect of residential externalities.

Lastly, note that due to the Iacoviello (2005)-type setup, the model includes two household types. The mechanisms do not work with a single household type. With one household type and a constant housing stock, equilibrium occupied housing volume is constant for all households. However, both channels require *changes* in occupied housing volume over time.

4 Calibrating the model

Next, I calibrate the model with US data to assess the strength of my mechanisms from a quantitative perspective. I create model regions with distinct spatial structures such that I can compare effects of interest rate changes in these regions. I select two US states with contrasting spatial structures as the sources of my model regions: California and Vermont. California is the US state with the highest level of both centralization and clustering according to the measurements in the empirical part of the paper, and therefore the state with the highest level of residential concentration. Vermont is the state with the lowest level of residential concentration.

Figure 1: Visualization of California: Location categories and housing volumes (2015)



Notes: Displayed is the Mollweide-projected shape (the Mollweide projection preserves relative areas but distorts angles) of California, obtained from the US Census Bureau, together with the 1 km×1 km grid layers "urban centers" (Melchiorri et al., 2024) and "functional urban areas" (Schiavina et al., 2019) (in the left panel) and residential built-up volume (Pesaresi and Politis, 2023b) (in the right panel), for 2015 on a 1 km×1 km grid. Both of the latter are derived from the Global Human Settlement Layer database.

Location categories. To allow for a simple exposition of the quantitative model results, I group locations into categories and assign location counts by category. For this procedure, I consult the Global Human Settlement Layer database. The database provides the layers *urban centers* (Melchiorri et al., 2024) and *functional urban areas* (Schiavina et al., 2019), both with a resolution of $1\,\text{km} \times 1\,\text{km}$ at the level of *grid cells*. Urban centers are defined as "contiguous grid cells with a density of at least 1,500 inhabitants per km^2 [...] and [...] at least 50,000 inhabitants" (Melchiorri et al., 2024). Functional urban areas are defined as "a set of contiguous [grid cells] that have at least 15% of their employed residents working in the city [center]" (Dijkstra et al., 2019). Note that I only cite the key characteristics here; the layers are produced using more involved definitions. The functional urban area layer is available for 2015, while the urban center layer is available at 5-year intervals. I choose the 2015 version of the urban center layer for consistency.

Combining the two layers, I obtain 3 location categories: urban center locations, periphery locations (representing parts of functional urban areas outside of urban centers), and rural locations (representing areas outside of functional urban areas, provided that they are not empty). The location categories are illustrated for California in the left panel of Figure 1.

Location counts. I count the number of grid cells by category in Vermont and California and scale these counts down for numerical feasibility. I create two model regions, *Region 1* and *Region 2,* based on Vermont and California. I also create a third region, *Region 3,* that I endow with the same total housing volume as Region 2, but distribute this housing volume uniformly across locations. Since Vermont only contains rural locations, Region 3 provides a more comparable counterpart to the California-based Region 2 which contains all three location categories. Moreover, Region 3 serves as a benchmark to later pinpoint effects that solely stem from the spatial distribution of housing while keeping a region's total amount of housing and area fixed.

Table 1: Summary statistics for model regions and US states: Location counts

Statistic	Region 1	Region 2	Region 3	Vermont	California
Total number of locations or cells	10	78	78	18,656	143,134
Urban center locations or cells	0	6	6	0	10,991
Periphery locations or cells	0	15	15	0	27,244
Rural locations or cells	10	57	57	18,656	104,899

Notes: Region 1 is based on Vermont; Region 2 and Region 3 are based on California. Region 3 has the identical setup as Region 2, but has its total housing volume uniformly distributed across locations. The numbers of locations in the model regions are normalized using the number of urban center grid cells in California. The grid cells refer to a $1\,\text{km} \times 1\,\text{km}$ grid for 2015 from the Global Human Settlement Layer database. The categorization follows definitions from Melchiorri et al. (2024) and Schiavina et al. (2019).

The location counts are summarized in Table 1. I set the number of urban center locations and periphery locations in Region 1 to 0, since there are no such grid cells in Vermont. Next, I normalize the number of urban center locations in Region 2 to 6, which yields clean ratios of data grid cell numbers across all categories in Vermont and California. With 18,656 rural grid cells in Vermont, the number of rural locations in Region 1 is 10, in relation to the 10,991 urban center cells in California represented by 6 locations ($6 \times 18{,}656/10{,}991 \approx 10$). The remaining numbers of locations by category and model region are calculated analogously: All model location numbers are approximately equal to data grid cell numbers multiplied by 6 and divided by 10,991.

Housing volumes. Next, I apply the GHSL-V layer (Pesaresi and Politis, 2023b), which provides me with information on residential built-up volume, to assign housing volumes to the model regions by location category. The GHSL-V layer is produced with satellite imagery from various sources, combining measures of built-up surface and building heights. Residential built-up volume is classified via machine learning and includes single-family housing, multi-family housing, mobile homes, and mixed-use housing. Manual validation indicates a classification accuracy of 87% for Northern America (see European Commission Joint Research Centre, 2023). The data are available at 5-year intervals and different resolutions. I use the 2015 version at a resolution of 1 km$\times$1 km for consistency with the location category layers. The residential built-up volume data are illustrated for California in the right panel of Figure 1.

I sum up residential built-up volume in Vermont and California for each of the three categories, as reported in Table 2. To translate these measurements into model units, I normalize the housing volume per location in the urban center locations of Region 2 to 1. Then, for Regions 1 and 2, I calculate the housing volume per location in the remaining categories relative to the normalized value of 1, using the housing volumes and grid cell numbers in Vermont and California. For every location of Region 3, I assign the region-wide average housing volume per location of Region 2, such that the spatial distribution of housing is uniform.

Table 2: Summary statistics for model regions and US states: Housing volumes

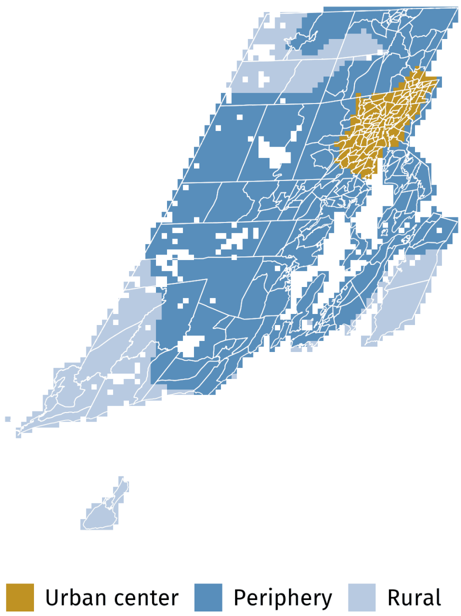
Statistic	Region 1	Region 2	Region 3	Vermont	California
Total housing volume, all categories	0.11	8.73	8.73	0.39 km^3	30.82 km^3
Urban center housing volume (total)	0	6	0.67	0 km^3	21.22 km^3
Periphery housing volume (total)	0	2.00	1.68	0 km^3	7.00 km^3
Rural housing volume (total)	0.11	0.73	6.38	0.39 km^3	2.60 km^3

Notes: Region 1 is based on Vermont; Region 2 and Region 3 are based on California. Region 3 has the identical setup as Region 2, but has its total housing volume uniformly distributed across locations. The model regions' housing volumes are normalized using the housing volumes of urban center grid cells in California. The grid cells refer to a 1 km$\times$1 km grid for 2015 from the Global Human Settlement Layer database. The categorization follows definitions from Melchiorri et al. (2024) and Schiavina et al. (2019). The housing volumes are derived from the GHSL-V layer (Pesaresi and Politis, 2023b). The two-digit rounding in the table, which might introduce apparent inconsistencies, is only used to display values.

Spatial household masses. Next, I calibrate the household mass parameter $\mu_n^{\mathcal{T}}$. Recall that this parameter describes household masses per unit of housing. I use $\mu_n^{\mathcal{T}}$ to externally calibrate a baseline spatial distribution of housing market tightness and hence prices. Thereafter, I fine-tune the spatial distribution of housing prices with ω_n, which I calibrate internally. I have 3 location categories in the model: urban center locations, which I denote as $\mathcal{C}$, periphery locations $\mathcal{P}$, and rural locations $\mathcal{L}$. I calibrate $\mu_n^{\mathcal{T}}$ (as well as ω_n thereafter) by location category, such that parameters by location category are equal across model regions.

Figure 2: Geospatial layering informs the calibration of spatially varying parameters

An example of the calibration layers
Visualization of Rhode Island, categorized cells and census tracts.



Notes: Displayed is the Mollweide-projected shape (the Mollweide projection preserves relative areas but distorts angles) of Rhode Island, obtained from the US Census Bureau, together with the 1 km × 1 km grid layers "urban centers" (Melchiorri et al., 2024) and "functional urban areas" (Schiavina et al., 2019) from the Global Human Settlement Layer database for 2015, and shapes of US census tracts (also derived from the US Census Bureau). The American Community Survey 5-Year Data provides information on household counts and owned housing values by census tract, using which I calibrate household masses and housing utility weights.

Using a geospatial version of the 2016–2020 American Community Survey 5-Year Data (ACS), I categorize US households into savers and borrowers and impute the number of savers and borrowers by location category (urban center, periphery, and rural). The ACS provides me with information on the number of homeowner and renter households at the census-tract level. I assign renter households to $\mathcal{B}$-type households. For homeowner households, I proxy for the characteristic "constrainedness" with whether a homeowner household pays more than 30% of its income on housing expenditures. This captures households who have high mortgage expenditures and are therefore likely to be constrained homeowners in the sense of my model. I categorize homeowner households who pay more than 30% of their income on housing expenditures as $\mathcal{B}$-type households and the remaining ones as $\mathcal{S}$-type households. I multiply by census-tract-level average household sizes to arrive at population counts.[6]

Next, I assign population counts to location categories. For this, I use the category layers introduced above and layer on top of that a map of US census tracts. Using Rhode Island as an example, I illustrate this layering in Figure 2. Rhode Island is the smallest US state in terms of

[6] I can only distinguish household sizes between homeowner households and renter households. In that sense, I assume household sizes to be equal for unconstrained and constrained homeowner households. A sensitivity analysis discussed later checks sensitivity of the main model results for most parameters, including $\mu_n^{\mathcal{T}}$.

area, allowing for clear visibility of spatial features. Note that I calibrate the model with data from contiguous US states to be consistent with the empirical part of the paper in which I can only use data from these states (except for New Hampshire due to missing data). "Contiguous" refers to all US states except for Alaska and Hawaii. Recall that my model regions reflect the spatial structures of Vermont and California, but other than that do not represent these states.

Table 3: Summary statistics for the calibration of household masses (United States)

	Urban center cells	Periphery cells	Rural cells
Unconstrained homeowner population	43,696,336	67,955,575	52,140,293
Constrained homeowner population	16,069,036	18,226,424	12,038,333
Renter population	51,337,503	31,015,460	23,433,938
Housing volume	$90.97\,\text{km}^3$	$94.26\,\text{km}^3$	$77.44\,\text{km}^3$

Notes: The counts are produced with the 2016-2020 American Community Survey 5-Year Data using information on the number of homeowner households (B25009EST2), the number of renter households (B25009EST10), and the number of "constrained" homeowner households who pay more than 30 % of their income on housing expenditures (B25106_CB_O_LT35 and B25106_CB_O_GT35), multiplied by average household sizes (homeowners: B25010EST2, renters: B25010EST3). I only count households located in contiguous US states, consistent with the empirical part of the paper, using shapefiles from the US Census Bureau. Moreover, the table lists the total housing volume (Pesaresi and Politis, 2023b) by location category, derived from the Global Human Settlement Layer database, as I define household masses $\mu_n^{\mathcal{T}}$ per unit of housing V_n.

For each census tract in the contiguous United States, I count the population number by assigned type. Then, I calculate the share of a census tract area that overlaps with each of the location category areas. I scale the shares to sum to unity after removing empty grid cells. Weighting the census-tract-level population counts with these shares, I assign the resulting imputed population counts to the respective location category and sum up the counts by location category and household type. I report the aggregated population counts in Table 3, including renters and constrained homeowners separately for illustration.

Table 3 also reports aggregated US housing volumes by location category, with which I can calibrate $\mu_n^{\mathcal{T}}$. I normalize $\mu_{n:n\in\mathcal{C}}^{\mathcal{S}}$, which amounts to 43,696,335 people divided by $90.97\,\text{km}^3$ of housing volume, to 1 and I calculate all other $\mu_n^{\mathcal{T}}$ relative to $\mu_{n:n\in\mathcal{C}}^{\mathcal{S}}$. This yields $\mu_{n:n\in\mathcal{P}}^{\mathcal{S}} = 1.50$, $\mu_{n:n\in\mathcal{L}}^{\mathcal{S}} = 1.40$, $\mu_{n:n\in\mathcal{C}}^{\mathcal{B}} = 1.54$, $\mu_{n:n\in\mathcal{P}}^{\mathcal{B}} = 1.09$, and $\mu_{n:n\in\mathcal{L}}^{\mathcal{B}} = 0.95$ as population mass parameters for an average US urban center cell, periphery cell, and rural cell.

Spatial housing utility weights. The remaining spatially varying parameter to be calibrated is the housing utility weight ω_n. It is standard in Iacoviello (2005)-type models to target the US national housing-wealth-to-GDP ratio with a spatially invariant housing utility weight. I target the same statistic here (5.43 as the 2018–2019 average), which I obtain from the Financial Accounts of the United States and the Bureau of Economic Analysis.[7] I choose 2018 and 2019 as years with a neutral state of the business cycle before the COVID recession, suitable for the representation of a steady state.

[7] I calculate the average ratio of nominal household real estate wealth (LM155035015.Q) over quarterly seasonally adjusted nominal GDP (A191RC).

This fixes one moment. I have 3 parameters, $\omega_{n:n\in\mathcal{C}}$, $\omega_{n:n\in\mathcal{P}}$, and $\omega_{n:n\in\mathcal{L}}$. I construct two additional housing-price-related moments to target. Using the ACS data, I retrieve census-tract-level median owner-occupied housing values.[8] For this calculation, I assign location categories to census tracts according to the location category with the highest area share in a census tract. I calculate the owner-population-weighted median housing value by location category and obtain as two additional targeted moments $P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{P}} = 1.27$ and $P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{L}} = 2.06$.

Other parameters. I now turn to the spatially invariant parameters. First, I calibrate the labor input weights $\alpha^{\mathcal{S}}$ and $\alpha^{\mathcal{B}}$, which correspond to steady-state labor income shares. Based on estimates from Kaplan et al. (2014), I calculate labor income for $\mathcal{S}$-type and $\mathcal{B}$-type households by assigning an income level of \$60,000 (annual, in 2010 dollars) to unconstrained homeowners ("non-hand-to-mouth"), \$50,000 to constrained homeowners ("wealthy hand-to-mouth"), and \$ 20,000 to renters ("poor hand-to-mouth"). Note that I cannot observe income by household type in the ACS. Aggregating (with ACS household counts instead of population counts), this yields $\alpha^{\mathcal{S}} = 0.68$, and due to normalization of the labor input weights, $\alpha^{\mathcal{B}} = 0.32$, which aligns with typical estimates for Iacoviello (2005)-type models.

Next, I set the household types' discount factors. Via the savers' Euler equation, the steady-state quarterly gross real interest rate is characterized by $R = 1/\beta^{\mathcal{S}}$. I set $\beta^{\mathcal{S}} = 0.9925$ for an annualized net real rate of 3%. Moreover, following Iacoviello et al. (2025), I set $\beta^{\mathcal{B}} = 0.9850$, which implies an annualized internal net real rate of 6% for $\mathcal{B}$-type households.

A mortgage loan-to-value ratio limit $\gamma = 90\%$ is standard (see, for example, Iacoviello, 2015); more importantly, it is consistent with my calibration target for the residential externality strength parameter ξ. For the macro-level strength of residential externalities, I cannot rely on values from the literature. Hence, I calibrate this parameter internally, targeting $\bar{B}^{\mathcal{B}}/\bar{Y}$, where bars denote regional values. This statistic is suitable because the strength of residential externalities determines $\mathcal{B}$-type housing demand particularly strongly: Externalities accrue to all households, but affect $\mathcal{S}$-type housing demand only to a small extent, as savers are unconstrained. Via the US National Mortgage Database, I can observe nationally aggregated information on mortgage debt and borrower characteristics, which allows me to obtain an empirical measure of $\bar{B}^{\mathcal{B}}$. Following Iacoviello and Neri (2010), I categorize borrowers as constrained whose loan-to-value ratio exceeds 80%. I observe the fraction of mortgage borrowers to whom this applies, as well as the total amount of mortgage debt. I calculate the amount of mortgage debt held by constrained borrowers as the total amount of mortgage debt times the fraction of borrowers with loan-to-value ratios above 80%. I cannot observe the mortgage balances of individual borrowers; I can only observe bins, for example, 80% to 90%, and what fraction of total borrowers belong to a bin. Hence, I implicitly assume here that unconstrained and constrained borrowers have identical mortgage debt on average.[9] The resulting targeted moment for 2018–2019 is $\bar{B}^{\mathcal{B}}/\bar{Y} = 0.33$. The

[8]Variable code: B25097EST1.
[9]This can be straightforwardly checked with loan-level datasets such as the Freddie Mac Single Family Loan-Level

weighted average loan-to-value ratio of constrained borrowers is 89.7% (using the fractions of borrowers that belong to the respective bins as weights), which aligns with $\gamma = 90\%$.

The remaining parameter that I calibrate internally is the preference weight for owner-occupied housing $\phi^{\mathcal{O}}$, where $\phi^{\mathcal{R}}$ is normalized to $1 - \phi^{\mathcal{O}}$. I target the share of housing occupied by renters out of total housing occupied by renters and constrained homeowners, that is, $\bar{V}^{\mathcal{B},\mathcal{R}} / (\bar{V}^{\mathcal{B},\mathcal{O}} + \bar{V}^{\mathcal{B},\mathcal{R}})$. I have the number of renters and constrained homeowners from the 2016–2020 American Community Survey 5-Year Data, and additionally use estimates of median housing size by ownership type to arrive at a data moment. From the American Housing Survey, I retrieve the median home size of renters in 2019, which amounts to $91\,\mathrm{m}^2$, and that of homeowners, which amounts to $167\,\mathrm{m}^2$ (note that these are not housing volumes and that I cannot distinguish by constrainedness of homeowners here). Aggregating, again with household counts instead of population counts, I get my last targeted moment $\bar{V}^{\mathcal{B},\mathcal{R}} / (\bar{V}^{\mathcal{B},\mathcal{O}} + \bar{V}^{\mathcal{B},\mathcal{R}}) = 0.58$.

For the elasticity of substitution between owner-occupied and rented housing, I rely on a standard estimate of 2 (see Ortega et al., 2011), such that $\eta = 0.5$. I set the labor supply disutility parameter δ to a standard value of 2, such that disutility is quadratic. Lastly, I choose a standard persistence of interest rate changes $\rho = 0.5$ and set $\sigma = 6.25 \times 10^{-4}$ such that a one-standard-deviation quarterly shock simulates an annualized shock of 25 basis points.

Matched moments and steady state. For the internal calibration, I use the method of simulated moments and minimize the Euclidean distance of equally weighted relative deviations between model moments and data moments. With 5 internally calibrated parameters and 5 targeted moments, I exactly match all moments.

To initialize the internal calibration, I calculate regional population masses $\bar{M}$ to weight regional steady-state model moments (note that I do not use regional indices for ease of notation). I obtain $\bar{M} = \sum_{n=1}^{N} (\mu_n^{\mathcal{S}} + \mu_n^{\mathcal{B}}) V_n$ via the regions' spatial structures and the externally calibrated $\mu_n^{\mathcal{T}}$ values. Regional variable $\bar{Z}^{\mathcal{T},\cdot}$ is defined as $\sum_{n=1}^{N} \mu_n^{\mathcal{T}} V_n Z_n^{\mathcal{T},\cdot}$, except for regional housing volume which is defined as $\bar{V} = \sum_{n=1}^{N} V_n$ and the regional housing price which is defined as $\bar{P} = \left(\sum_{n=1}^{N} V_n P_n\right) / \bar{V}$; the regional rental price is defined analogously. The spatial housing price ratios $P_{n:n\in\mathcal{C}} / P_{n:n\in\mathcal{P}}$ and $P_{n:n\in\mathcal{C}} / P_{n:n\in\mathcal{L}}$ are not defined for Region 1, so for this statistic the internal calibration only uses information from Region 2. I do not include the artificial Region 3 in the internal calibration, hence the bracketed values in Table 4 which summarizes steady state statistics. The resulting internally calibrated parameters are $\xi = 0.130$, $\phi^{\mathcal{O}} = 0.483$, $\omega_{n:n\in\mathcal{C}} = 0.074$, $\omega_{n:n\in\mathcal{P}} = 0.033$, and $\omega_{n:n\in\mathcal{L}} = 0.021$.

The steady state statistics provide a first set of quantitative model results. The regional consumption shares of $\mathcal{S}$-type and $\mathcal{B}$-type households are close to identical in the three regions,

Dataset. In the years of focus (2018 and 2019), this holds quite precisely, except for very low loan-to-value ratios. Intuitively, higher loan-to-value ratios of constrained borrowers with low incomes are accompanied by lower housing values, such that mortgage debt is quite similar across the loan-to-value ratio distribution. Note that these are only mortgage originations, not the total outstanding mortgage debt. I use the NMDB exactly because it gives me information on that, and because it provides nationally aggregated values, as opposed to datasets that only cover a fraction of the mortgage market such as the Freddie Mac dataset.

as they are primarily determined by labor income shares. The housing volume shares differ, mostly due to borrowers' reduced steady-state housing volumes in urban center locations (which result from both location preferences and residential externalities). Notice that Regions 1 and 3, although being different in their spatial setup, display quite similar steady state statistics. This already hints at the spatial channels only being notably strong in the high-concentration Region 2. Moreover, recall that stronger residential externalities imply lower steady-state housing prices due to a free-riding effect: Residential externalities allow for obtaining reasonable housing service flows while living in small residential units, lowering steady-state housing demand. The spatial housing price ratios $P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{P}}$ and $P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{L}}$ are larger in Region 3 than in Region 2, since the price-increasing force of housing utility weights in the urban centers of Region 3 acts (almost) without the price-decreasing force of the externalities.

Table 4: Steady state statistics for the baseline model

Variable	**Region 1**	**Region 2**	**Region 3**	**Type of statistic**	**Moment**	**Target**
$\bar{M}$	0.26	22.14	(21.07)	Weight for MSM	–	–
$\bar{P}\bar{V}/\bar{Y}$	2.76	5.46	(3.45)	Targeted moment	5.43	5.43
$P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{P}}$	–	1.27	(1.97)	Targeted moment	1.27	1.27
$P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{L}}$	–	2.05	(3.38)	Targeted moment	2.05	2.06
$\bar{B}^{\mathcal{B}}/\bar{Y}$	0.32	0.33	(0.38)	Targeted moment	0.33	0.33
$\bar{V}^{\mathcal{B},\mathcal{R}}/(\bar{V}^{\mathcal{B},\mathcal{O}}+\bar{V}^{\mathcal{B},\mathcal{R}})$	0.58	0.58	(0.58)	Targeted moment	0.58	0.58
$\bar{C}^{\mathcal{S}}/\bar{Y}$	0.69	0.69	0.69	Model outcome	–	–
$\bar{C}^{\mathcal{B}}/\bar{Y}$	0.31	0.31	0.31	Model outcome	–	–
$\bar{V}^{\mathcal{S},\mathcal{O}}/\bar{V}$	0.70	0.84	0.71	Model outcome	–	–
$\bar{V}^{\mathcal{B},\mathcal{O}}/\bar{V}$	0.13	0.07	0.12	Model outcome	–	–
$\bar{V}^{\mathcal{B},\mathcal{R}}/\bar{V}$	0.18	0.09	0.17	Model outcome	–	–

Notes: Residential concentration is high in Region 2 (based on California), medium in Region 3 (Region 2 with a uniform spatial distribution of housing), and low in Region 1 (based on Vermont). $\mathcal{S}$ refers to savers, $\mathcal{B}$ refers to borrowers, $\mathcal{O}$ refers to owner-occupied housing, and $\mathcal{R}$ refers to rented housing. Locations, indexed by n, are categorized into "urban center" $\mathcal{C}$, "periphery" $\mathcal{P}$, and "rural" $\mathcal{L}$. Variables with bars refer to regional values. The variables are M for population masses, P for housing prices, V for housing volume, Y for output, $B^{\mathcal{B}}$ for mortgage borrowing, and C for consumption. The internal calibration uses the method of simulated moments (MSM), with 5 targets for 5 parameters, minimizing the Euclidean distance of equally weighted relative deviations from model moments to data moments. The model moments of Region 1 and Region 2 are weighted with the respective regional population mass. The artificial Region 3 is not used for the internal calibration. The two-digit rounding in the table, which might introduce apparent inconsistencies, is only used to display values.

5 Quantitative model results

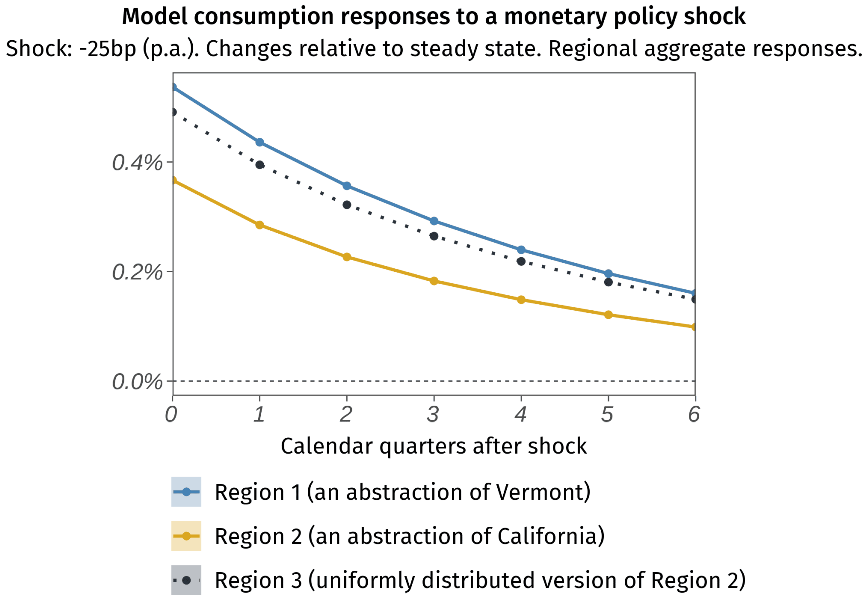
I have constructed the three model regions such that they are identical in terms of parameters and only differ exogenously in their spatial structures. I now simulate interest rate changes in the three model regions separately.

5.1 Baseline impulse responses

Regional responses. Figure 3 displays the regional consumption responses in the three model regions to a 25-basis-point unexpected interest rate decrease. See Appendix A4 for regional responses of all variables and corresponding economic intuition.

In Region 2, the high-concentration region based on California, consumption responds considerably less than in Regions 1 and 3. Compared to the low-concentration Region 1 based on Vermont, the consumption response in Region 2 is dampened by 31.5% on impact: The response in Region 2 is 0.37% and the response in Region 1 is 0.54%, such that the response is dampened by $1-(0.37\%/0.54\%) \approx 31.5\%$ in Region 2 relative to Region 1. This dampening effect remains highly persistent and reaches 38% after 6 calendar quarters. The effect is similar when comparing Regions 2 and 3 at 25% on impact and at 34% after 6 calendar quarters. Evidently, for the channels to become notably strong, a large amount of housing has to be located centrally, as in Region 2.

Figure 3: The consumption response is dampened in the high-concentration region



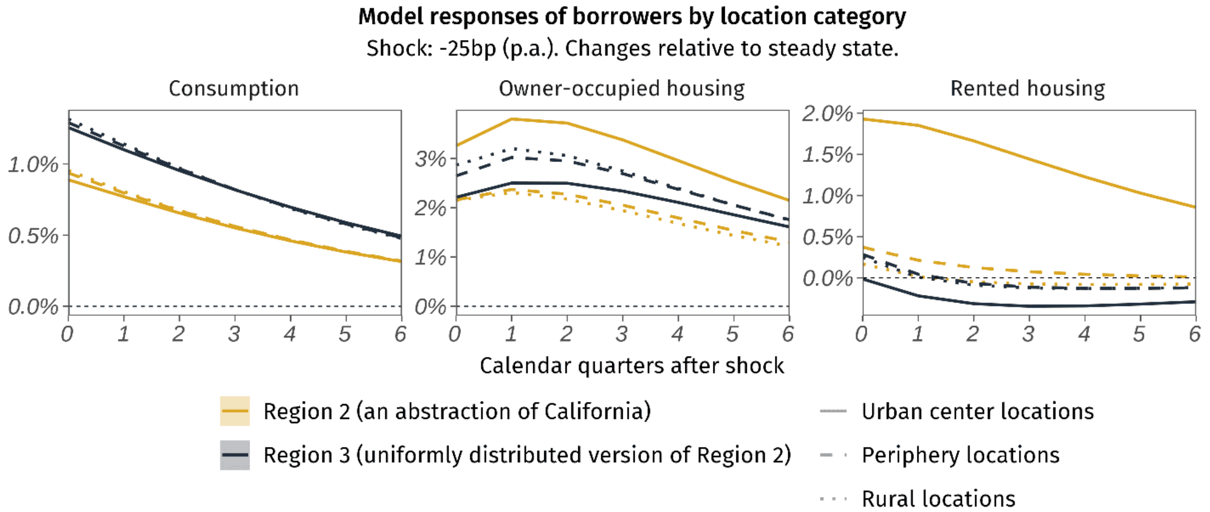
Notes: Residential concentration is high in Region 2, medium in Region 3, and low in Region 1.

Note that Regions 2 and 3 have the same (naive) measure of residential density, that is, the same total amount of housing volume divided by total area. Location preferences and residential externalities give rise to economic effects that depend on the spatial distribution of housing in a region. It is not enough to look at regional residential density. I will confirm this result in the data in the empirical part of the paper.

Sensitivity analysis. Next, I summarize the results from a sensitivity analysis, documented in Appendix A5. I start from the baseline calibration and report the dampening effect on impact for total regional consumption in Region 2 versus Regions 1 and 3 as a function of parameter values, changing one parameter at a time within a reasonable range (that is, until I receive no output or the parameter or response exceeds a realistic level).

For most parameters, the dampening effect is not particularly sensitive to changes in parameter values, and many parameters leave room for a stronger dampening effect. For the "worst (realistic) case", I would have to go toward linear disutility of labor supply ($\delta \to 1$). In that case, wages adjust so little to clear the labor market that consumption responses are quite weak in general (this refers to borrowers; savers are still on their Euler equations). Even then, I get a dampening effect of 10% on impact. The only other parameter that is associated with high sensitivity is the savers' productivity level, which is quite natural, as it directly determines labor income shares.

Figure 4: High-density urban centers are the sources of the dampening effect



Notes: Residential concentration is high in Region 2 and medium in Region 3. The urban center locations of Region 2 have a high residential density, while the urban center locations of Region 3 have a comparably low residential density. The image shows per-capita responses.

Location-specific responses. To enable a more detailed investigation of the main results, Figure 4 displays location-specific consumption and housing responses of borrowers. The urban center locations of Region 2, featuring particularly high housing volumes, generate strong residential externalities, leading to notably more positive housing responses of borrowers (regarding both owner-occupied and rented housing). In contrast, the urban center locations of Region 3 generate comparably weak externalities, and borrowers' housing demand responses become less positive due to a dominating effect of the location preference channel.

Consumption responses are almost fully equalized across locations within regions, as opposed to housing responses. This results from spatial equilibrium linkages between locations through region-wide goods and labor markets. High steady-state housing prices and amplified housing responses in the urban center locations of Region 2 give rise to a strong dampening effect on consumption. Regional goods and labor markets carry this effect to peripheral and rural locations: Location-level consumption of borrowers primarily increases with region-wide wages.

5.2 Decomposing the channels

To determine how much of the total dampening effect can be attributed to location preferences and how much to residential externalities, I implement two recalibrations of the model. "Recalibration" in this context means that I conduct a new internal calibration, rather than changing parameters individually as in the sensitivity analysis.

This exercise furthermore serves to illustrate that both spatial features are required for the model to match the US national and spatial data moments.

Recalibration 1: Only location preferences. In Recalibration 1, I calibrate the model with the same procedure as before, but set $\xi = 0$ beforehand. Hence, I do not target the ratio of constrained mortgage debt to GDP. This immediately leads to the weakness of this model version, documented in Table 5. The ratio $\bar{B}^{\mathcal{B}}/\bar{Y}$ is far from the empirical (national) value of 0.33 in Region 2, where it is almost twice as high as the empirical value. Without residential externalities, borrowers' steady-state housing sizes become unrealistically large due to a lack of free-riding on external housing service flows, which increases constrained mortgage debt. The latter is pinned down by borrowers' owner-occupied housing volumes and housing prices, where housing prices are close to identical as in the main model version, as all housing-price-related moments are targeted. With "unrealistic", I refer to owner-occupied housing sizes that are inconsistent with the empirical value of $\bar{B}^{\mathcal{B}}$, given $\gamma = 90\%$ and $\bar{V}^{\mathcal{B},\mathcal{R}}/\left(\bar{V}^{\mathcal{B},\mathcal{O}} + \bar{V}^{\mathcal{B},\mathcal{R}}\right) = 0.58$.

Table 5: Steady state statistics, Recalibration 1: Only location preferences

Variable	Region 1	Region 2	Region 3	Type of statistic	Moment	Target
$\bar{P}\bar{V}/\bar{Y}$	2.76	5.46	(3.31)	Targeted moment	5.43	5.43
$P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{P}}$	–	1.27	(1.38)	Targeted moment	1.27	1.27
$P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{L}}$	–	2.06	(2.25)	Targeted moment	2.06	2.06
$\bar{V}^{\mathcal{B},\mathcal{R}}/\left(\bar{V}^{\mathcal{B},\mathcal{O}} + \bar{V}^{\mathcal{B},\mathcal{R}}\right)$	0.58	0.58	(0.58)	Targeted moment	0.58	0.58
$\bar{B}^{\mathcal{B}}/\bar{Y}$	0.32	0.63	0.38	Model outcome	–	(0.33)

Notes: Residential concentration is high in Region 2 (based on California), medium in Region 3 (Region 2 with a uniform spatial distribution of housing), and low in Region 1 (based on Vermont). See Table 4 for variable definitions and details on the internal calibration. The two-digit rounding in the table, which might introduce apparent inconsistencies, is only used to display values.

I simulate an unexpected interest rate cut and plot regional consumption responses in the second panel of Figure 5. Location preferences alone can already account for a large part of the dampening effect: The impact response of regional consumption is dampened by 19% in Region 2 relative to Region 1 and by about 14% relative to Region 3. Note, however, that the effect fades away quickly, as it is based on housing transactions that are fueled by the rate cut. As the interest rate reverts toward steady state, the dampening effect diminishes.

Recalibration 2: Only residential externalities. In the second recalibration, I remove location preferences by using a single spatially invariant housing utility weight ω. The resulting spatial housing price ratios are starkly at odds with the data, see Table 6. In Region 2, housing prices in urban center locations amount to a bit more than half of those in periphery locations and rural locations. Regarding housing prices, location preferences constitute a counteracting force to residential externalities that ensures realistic spatial housing price distributions.

Moreover, the ratio of constrained mortgage debt to GDP in Regions 1 and 3 is unrealistically large compared to the data, as well as the ratio of housing wealth to GDP (even though the data moments are matched as population-weighted averages) – a further weakness of this recalibration. With a spatially invariant ω, peripheral and rural housing prices rise mechanically, inflating housing prices and mortgage debt in Regions 1 and 3 compared to the baseline model.

Table 6: Steady state statistics, Recalibration 2: Only residential externalities

Variable	Region 1	Region 2	Region 3	Type of statistic	Moment	Target
$\bar{P}\bar{V}/\bar{Y}$	7.11	5.41	(6.80)	Targeted moment	5.43	5.43
$\bar{B}^{\mathcal{B}}/\bar{Y}$	0.79	0.33	(0.73)	Targeted moment	0.33	0.33
$\bar{V}^{\mathcal{B},\mathcal{R}}/(\bar{V}^{\mathcal{B},\mathcal{O}}+\bar{V}^{\mathcal{B},\mathcal{R}})$	0.58	0.58	(0.58)	Targeted moment	0.58	0.58
$P_{g:g\in\mathcal{C}}/P_{n:n\in\mathcal{P}}$	–	0.57	0.86	Model outcome	–	(1.27)
$P_{n:n\in\mathcal{C}}/P_{n:n\in\mathcal{L}}$	–	0.58	0.96	Model outcome	–	(2.06)

Notes: Residential concentration is high in Region 2 (based on California), medium in Region 3 (Region 2 with a uniform spatial distribution of housing), and low in Region 1 (based on Vermont). See Table 4 for variable definitions and details on the internal calibration. The two-digit rounding in the table, which might introduce apparent inconsistencies, is only used to display values.

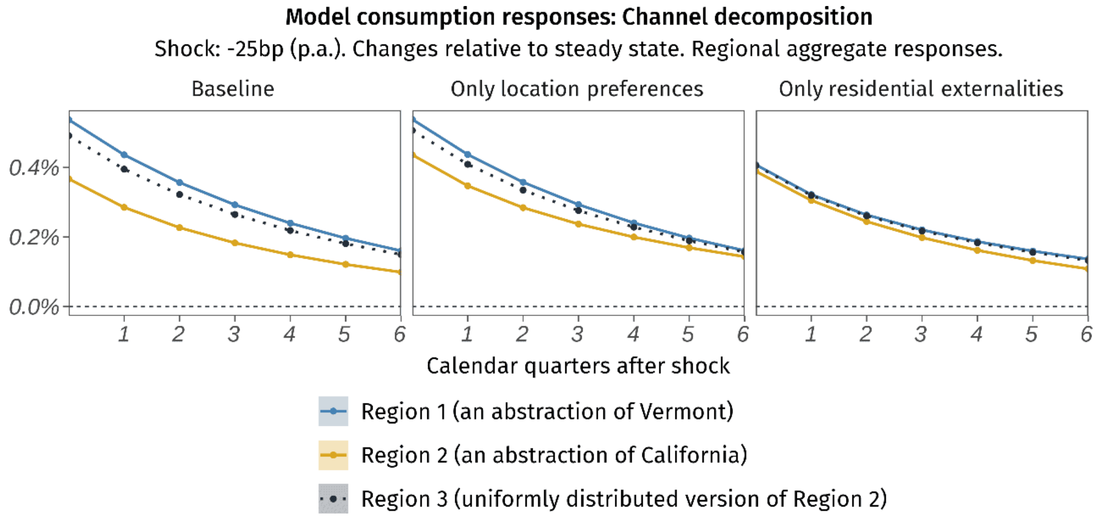
Again, I simulate an unexpected interest rate cut, see the third panel of Figure 5. The impact response of regional consumption is now dampened by 5% in Region 2 relative to Region 1 and by 4% relative to Region 3. However, the effect due to externalities is quite persistent, reflecting the intertemporal-smoothing nature of the externality channel. After 6 calendar quarters, the effect amounts to 21% and 18%. As housing is durable, housing volume responses are endogenously persistent. Due to this persistence, the dampening effect from the externality channel, which depends on the strength of housing volume responses, is carried over into future periods, even into periods in which the interest rate is, practically speaking, back at its steady-state level (which is the case in the 6th calendar quarter after the shock).

Lastly, note that the combined effect from Recalibrations 1 and 2 is smaller than the total effect in the baseline calibration: As discussed in Section 3, the two channels reinforce each other.

5.3 Alternative model setups

There are, at this point, two open questions: First, since I emphasized spatial equilibrium effects through region-wide market linkages, how important are these effects? Second, do I need spatial structure *at all,* or could a model version without spatial structure deliver the same results? I answer these questions with two alternative model setups.

Figure 5: The dampening effect is predominantly driven by location preferences



Notes: Residential concentration is high in Region 2, medium in Region 3, and low in Region 1.

Removing spatial equilibrium effects. In this model setup, I eliminate spatial equilibrium feedbacks to examine how much they contribute to the total dampening effect. I adjust the consumption goods and labor market clearing conditions such that

$$\mu_n^{\mathcal{S}} V_n C_{t,n}^{\mathcal{S}} + \mu_n^{\mathcal{B}} V_n C_{t,n}^{\mathcal{B}} = Y_{t,n} \quad \text{for} \quad n = 1, ..., N, \tag{37}$$

$$L_{t,n}^{\mathcal{T},\mathcal{F}} = \mu_n^{\mathcal{T}} V_n L_{t,n}^{\mathcal{T}} \quad \text{for} \quad \mathcal{T} \in \{\mathcal{S}, \mathcal{B}\} \quad \text{and} \quad n = 1, ..., N, \tag{38}$$

where production is location-specific:

$$Y_{t,n} = \left(L_{t,n}^{\mathcal{S},\mathcal{F}}\right)^{\alpha^{\mathcal{S}}} \left(L_{t,n}^{\mathcal{B},\mathcal{F}}\right)^{\alpha^{\mathcal{B}}}. \tag{39}$$

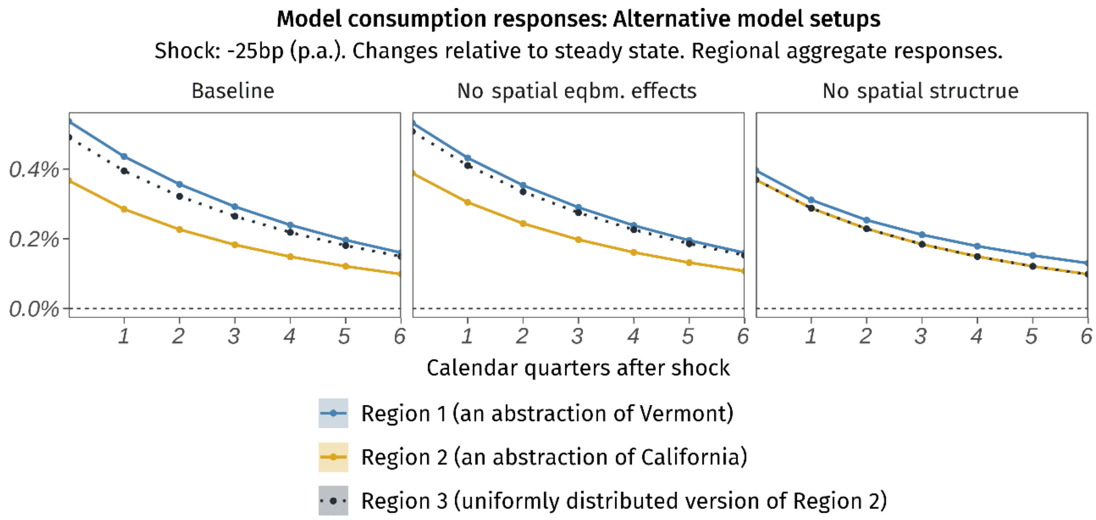
All markets now clear at the location level, with associated location-specific wage rates. Conceptually, the difference compared to the baseline model version is quite large: Locations are now fully isolated from each other (except regarding financial markets).

However, quantitatively, spatial equilibrium feedbacks are not essential for the results. To arrive at quantitative results, I repeat the calibration procedure from the baseline model. The second panel of Figure 6 shows the resulting total regional consumption responses. The response in Region 2 relative to Regions 1 and 3 is dampened by 27% and 24% on impact without spatial equilibrium effects, which is similar to the dampening effects obtained with spatial equilibrium feedbacks in the baseline model. This result is attributable to the large population share living in the urban center locations of Region 2. With most of the population living in these locations, it does not matter that much in the aggregate if the strong dampening effect does not spill over to peripheral and rural locations.

Removing spatial structure. In this model setup, I fully remove spatial structure to check whether such a model can also generate the main results. I effectively eliminate all n subscripts such that the model equations are defined at the regional level. Hence, in the calibration, I use spatially invariant $\mu^{\mathcal{T}}$ values and a spatially invariant ω value (all of which are equal for all model regions). The regions only differ in $\bar{V}$ and therefore also $\bar{X}$. Any differences in impulse responses can only result from externalities, since there is no spatial variation in housing utility weights and therefore no active location preference channel.

The resulting impulse responses are presented in the third panel of Figure 6. There is a dampening effect but, first, it is much weaker than in the baseline model; second, it is equal for Region 2 and Region 3 which is at odds with empirical results that I present in the following. In that sense, these results are unrealistic, which means that it is essential to explicitly model spatial structure in the context of this paper. I proceed with the empirical analysis to determine what "realistic" means regarding impulse responses.

Figure 6: Spatial eqbm. effects are not essential; spatial structure is essential



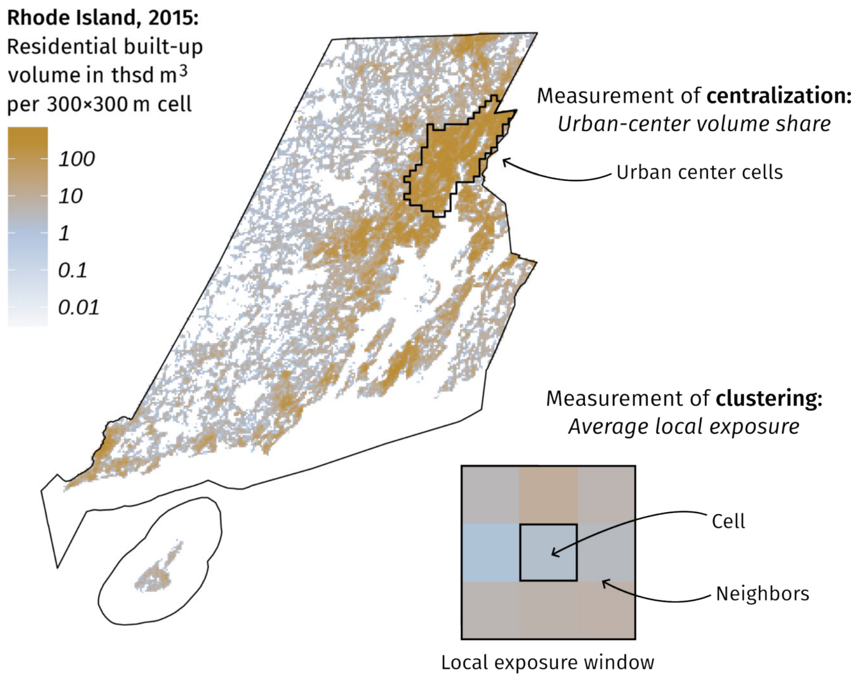
Notes: Residential concentration is high in Region 2, medium in Region 3, and low in Region 1.

6 Measuring residential concentration in the data

I have shown that a monetary business cycle model with spatial structure and two standard spatial economic features, location preferences and residential externalities, generates the result that residential concentration dampens the transmission of interest rate changes to household consumption. The two measures of residential concentration defined in Section 3, centralization and clustering, reflect the two spatial features.

Using the previously introduced geospatial data, I can empirically measure centralization and clustering to test whether the dampening effect that I find in the model is observable in the data. I work with data from US and Eurozone regions to exploit regional variation in residential concentration for my estimation. For the United States, one region is one state, while for the Eurozone, one region is one country, except for Germany, for which I can also use states. These constraints stem from the availability of high-frequency data that I need for this analysis.

Figure 7: Illustration of the measurement of centralization and clustering



Notes: Displayed is the Mollweide-projected shape (the Mollweide projection preserves relative areas but distorts angles) of Rhode Island, obtained from the US Census Bureau, together with residential built-up volume (Pesaresi and Politis, 2023b) in 2015 on a 300 m × 300 m grid from the Global Human Settlement Layer database (aggregated from the original 100 m × 100 m grid). For each grid cell, I measure exposure to residential built-up volume via local exposure windows. The baseline measurement features a 3×3 window and covers local exposure up to 636 m. I also use different window sizes in robustness checks. The image also illustrates 2015 urban center cells from a 1 km × 1 km grid (Melchiorri et al., 2024) used for the measurement of centralization.

Definitions of empirical measures. The empirical measure of residential centralization is straightforward. Using the 1 km × 1 km urban center layer and residential built-up volume layer from the Global Human Settlement Layer database, I measure residential centralization as the share of residential built-up volume in a region r that is located in urban center cells in time period t, following the definition from Section 3:

$$\text{Residential centralization}_{r,t} = \left. \frac{\sum_{\text{Cell}} \text{Volume}_{\text{Cell},\,t} \,\big|\, \text{Cell} \in \text{Urban center cells}}{\sum_{\text{Cell}} \text{Volume}_{\text{Cell},\,t}} \right|_{\text{Cell} \in r}. \tag{40}$$

Note that residential centralization describes the volume-weighted average centrality in a region, where centrality is an indicator variable, being equal to one if a cell is an urban center cell. In robustness checks, I replace the urban center layer with the functional urban area layer (only available for 2015) and use built-up surface instead of built-up volume (also for the measure of residential clustering described below). Urban center boundaries and residential built-up volume are available at 5-year intervals. The estimation will be at quarterly frequency, for which I linearly interpolate between spatial measurements over time. Urban center cells are highlighted in the illustrative Figure 7, again with Rhode Island for clear visibility of spatial features.

For the empirical measure of residential clustering, I have to go into more detail. Residential externalities accrue at spatially small scales, best described by neighborhoods. According to measurements of residential externalities' spatial decay from Rossi-Hansberg et al. (2010), Ahlfeldt et al. (2015), and Diamond and McQuade (2019), externalities are primarily generated within 300 m distance and have decayed close to zero after about 1 km distance. To accurately measure residential clustering and therefore the implied residential externalities, I apply higher-resolution versions of the Global Human Settlement Layer. The finest available level is 100 m×100 m, which I have to aggregate to 300 m×300 m for computational feasibility. Robustness checks discussed later indicate that this aggregation does not affect the results.

Then, I measure *local exposure* to residential built-up volume for every grid cell (in the spirit of the classic urban sprawl index from Burchfield et al., 2006).[10] I define local exposure as the sum of residential built-up volume in the respective grid cell and some specified neighbors:

$$\text{Local exposure}_{\text{Cell},\,t} = \text{Volume}_{\text{Cell},\,t} + \textstyle\sum_{\text{Neighbor}} \text{Volume}_{\text{Neighbor},\,t}. \tag{41}$$

This is illustrated in Figure 7. In the baseline measurement, local exposure refers to a window of immediate neighbors and therefore spans 3×3 cells, that is, 900 m×900 m. The maximum distance between the midpoint of such a window and the edge of the window is 636 m, which should capture most of residential externalities. I conduct robustness checks with 1×1, 5×5, and 7×7 local exposure windows. If a local exposure window overlaps with a region's border, I do not exclude the overlapping cells from this window.

In the next step, I aggregate local exposures to obtain a regional measure of residential clustering. Following the definition from Section 3, this is the volume-weighed average of local exposures:

$$\text{Residential clustering}_{r,\,t} = \left.\frac{\sum_{\text{Cell}} \text{Volume}_{\text{Cell},\,t} \times \text{Local exposure}_{\text{Cell},\,t}}{\sum_{\text{Cell}} \text{Volume}_{\text{Cell},\,t}}\right|_{\text{Cell} \in r}. \tag{42}$$

In Appendix B1, I compare the two spatial measures with a naive measure of residential density (total residential built-up volume divided by total area) in descriptive illustrations. For both measures, I find a mildly positive correlation both across regions and over time to residential density. The mere mild correlations reflect that the naive measure does not take into account the spatial distribution of housing.

The centralization measures for US states appear to involve substantial measurement error in some instances: There are visible outliers in terms of the change in centralization over time, with implausibly stark increases in centralization at 5-year intervals. Note that it is highly involved to define urban centers (for details, see Melchiorri et al., 2024). For the main specification with

[10] Note that in the model $X_n = \xi V_n$ for simplicity, whereas in the data I take spatial spillovers between grid cells into account.

residential centralization, I exclude states for which measurement error is particularly likely, that is, states for which residential centralization changed by more than 5.5 percentage points between 2000 and 2015 at 5-year intervals (these are outliers via Tukey's IQR method with factor 1.5). I provide a robustness check with these states (Montana, North Dakota, South Dakota, and Utah) being included. The additional robustness check with functional urban area boundaries is also important to counteract concerns here. This measure of is broader, such that measurement error should be smaller, with the downsides being that the boundaries are only available for 2015 and that they also include peripheral cells.

7 Empirical framework

I now use the residential concentration measures to see whether, as my model predicts, unexpected interest rate changes exhibit dampened effects in high-concentration regions.

Specification. I use the spatial measures as state variables in a state-dependent Jordà (2005) local projections framework (see, for example, Gonçalves et al., 2024). This empirical setup allows me to estimate the effects of identified monetary policy shocks as a function of residential centralization or residential clustering. To set up the local projections, I define that in calendar quarter t, the lagged spatial measure $x_{r,t-1}$ is assigned to region r. I estimate

$$\begin{aligned} y_{r,t+h} - y_{r,t-1} = \alpha_r + \beta_h^{(1)} m_t + \beta_h^{(2)} x_{r,t-1} + \beta_h^{(3)} m_t x_{r,t-1} \\ + \gamma_h^{(1)\prime} A_{r,t-1} + \gamma_h^{(2)\prime} m_t A_{r,t-1} + \sum_{k=1}^{K} \gamma_h^{(3)\prime} B_{r,t-k} + \varepsilon_{r,t+h}. \end{aligned} \tag{43}$$

The regional outcome variable $y_{r,t+h}$ is log-transformed. A monetary policy shock m_t affects the entire US or Eurozone. The coefficient of interest is the interaction coefficient $\beta_h^{(3)}$, which quantifies heterogeneity in the response to a shock depending on $x_{r,t-1}$. The shock and the spatial measure are included as separate regressors with coefficients $\beta_h^{(1)}$ and $\beta_h^{(2)}$ to correctly attribute interaction effects to $\beta_h^{(3)}$. The first vector of controls $A_{r,t-1}$ includes potential regional confounders and is interacted with the shocks. The second vector of controls $B_{r,t-k}$ includes a standard set of lagged controls. Control variables are described in detail below. The region fixed effect α_r filters out region-specific trends in the time paths of outcome variables. The regression residual is $\varepsilon_{r,t+h}$. Driscoll and Kraay (1998) standard errors ensure robustness of regression residuals to cross-sectional and autocorrelation.

I now discuss the variables that I employ in the estimation. Data sources are reported in Appendix B2 and summary statistics are reported in Appendix B3.

Shocks. For the United States, I combine monetary policy shock series from Aruoba and Drechsel (2025) and Bügel et al. (2024) that are both based on the methodology of the canonical narrative Romer and Romer (2004) shocks. The Aruoba and Drechsel (2025) shocks improve the original

Romer and Romer (2004) shocks by using natural language processing on text documents prepared by Federal Reserve economists. This series of conventional monetary policy shocks ends with the zero-lower-bound period after 2008. The Bügel et al. (2024) unconventional monetary policy shocks are designed to continue the Romer and Romer (2004)-type shock identification from 2009 to 2015 based on shadow rate estimates from Wu and Xia (2016). One shock relates to one Federal Open Market Committee meeting.

For the Eurozone, I use a series from Gulyas et al. (2024) that is based on high-frequency identified shocks from Altavilla et al. (2019). For consistency with the US shock series, a narrative measure of shocks would be more appropriate, but is not available to the best of my knowledge. The Gulyas et al. (2024) shocks use high-frequency surprises around ECB Governing Council meetings to the 6-month Overnight Index Swap (OIS) rate from Altavilla et al. (2019). The 6-month OIS rate is the fixed rate in a swap contract tied to the compounded overnight unsecured rate over the following six months, and serves as a market-based measure of expectations about the ECB's policy rate path. One shock corresponds to one ECB Governing Council meeting.

I temporally aggregate shocks at the quarterly level, with one quarterly shock being defined as the sum of all shocks within a calendar quarter. I use the same time horizon for the US and Eurozone shocks to run estimations under the same global economic conditions. The US monetary policy shocks bound this time span from above at 2015 Q4, while the Eurozone shocks bound this time span from below at 2000 Q2 (taking into account lags of control variables that I will discuss shortly). In robustness checks, I also use shock series from Jarociński and Karadi (2020) for both the United States and the Eurozone, where I trim the shock series consistent with the baseline.

Outcome variables. In the main estimation for the US, I use quarterly state-level post-government income as the outcome variable. For consistency with the model, I would ideally like to use high-frequency regional consumption data, but these are not available to the best of my knowledge. Even though the Consumer Expenditure Surveys provide quarterly consumption data, I do not use these data here, as "the estimates are calculated from a relatively small sample of predominantly urban areas" (see the documentation). I deflate income using the census-region-level Consumer Price Index (the 4 US census regions are Northeast, Midwest, South, and West). I use a version of the Consumer Price Index without shelter expenditures in a robustness check.[11] In an alternative estimation, I use *annual* data on US-state-level consumption.

For German states, Lehmann and Wikman (2025) provides quarterly real GDP estimates. Such high-frequency regional data are only available for Germany among all Eurozone countries. Accordingly, I use country-level quarterly real GDP data for the remaining countries. I consider German states and the remaining countries separately in a robustness check.

Control variables. I control for a standard set of lagged variables through $B_{r,t-k}$: $K = 4$ lags of the outcome variable; the shock; US-level or Eurozone-level inflation rates, that is, the inflation

[11] Here, I also exclude "real estate and rental and leasing" from total state-level income (which is, however, a small category; it amounts to 1-2% of total income and only reflects labor and proprietor earnings in real estate activities).

rates at the level of spatial aggregation primarily relevant to the central banks; and the effective federal funds rate for the US or the EONIA (Euro Overnight Index Average) rate for the Eurozone, where for the zero-lower-bound period 2009 to 2015, I use the respective shadow rates from Wu and Xia (2016) and Wu and Xia (2020). I also consider 3 and 5 lags in robustness checks.

Moreover, through $A_{r,t-1}$ I filter out confounding variation by controlling for variables that are potentially correlated with residential concentration and could be relevant for monetary policy transmission: sectoral composition, demographics, and housing market characteristics. In robustness checks, I exclude groups of control variables one at a time.

My model includes sectorally unspecified consumption goods. As different sectors might have varying sensitivities to monetary policy shocks (see, for example, Galesi and Rachedi, 2019), I control for the income share (US) or gross-value-added share (Eurozone) of the construction sector, the manufacturing sector, and the primary sector; with the income or gross-value-added share of the service sector constituting the reference category. Additionally, since demographics are not part of my model, but relevant for monetary policy (see, for example, Juselius and Takáts, 2021), I control for the shares of people older than 64 and younger than 20, with the share of people between 20 and 64 constituting the reference category.

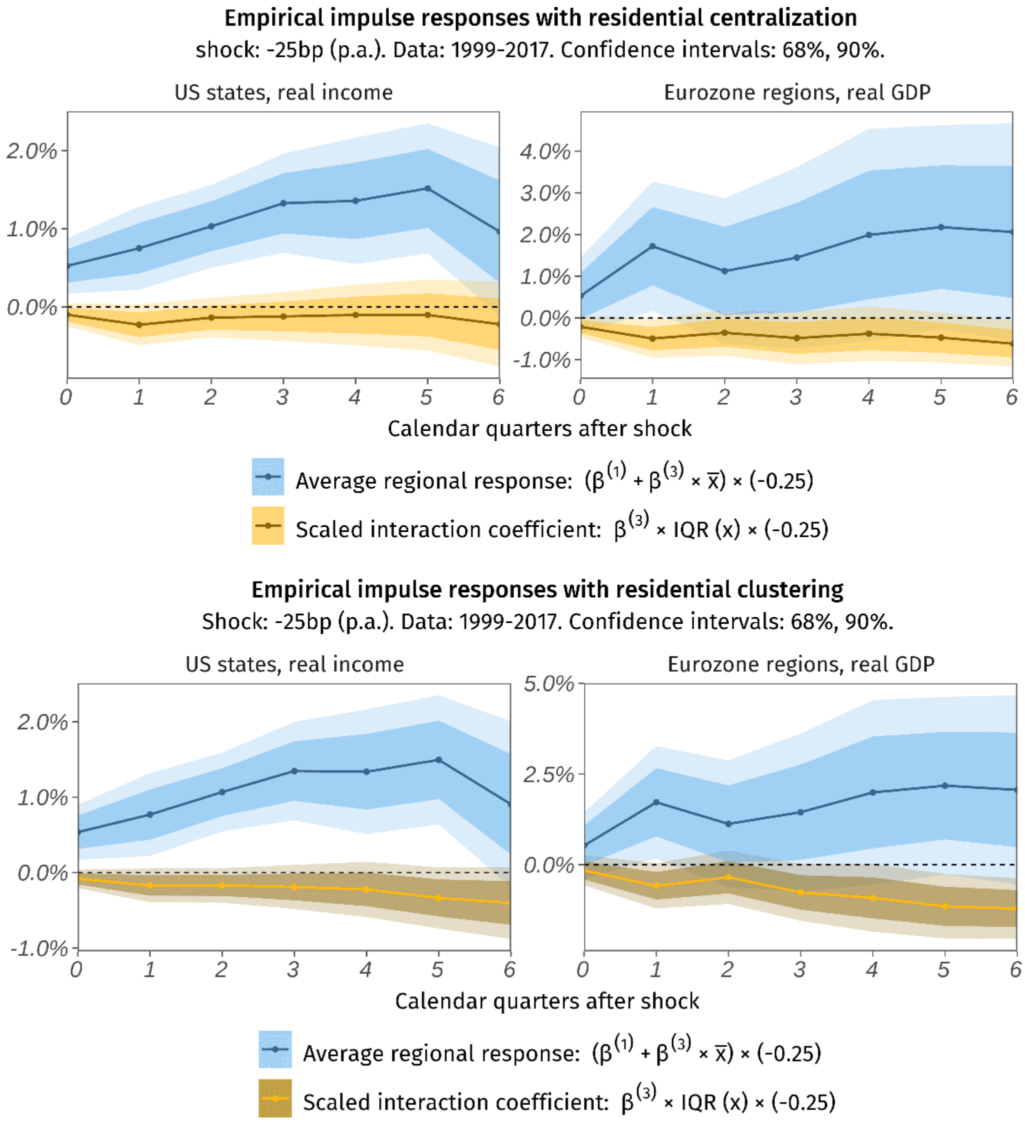
With regard to housing market characteristics controls, I control for the residential share of total built-up volume, which I extract from the Global Human Settlement Layer data, to filter out potentially confounding variation in residential housing market sizes. Moreover, I control for the elasticity of housing construction. For the United States, I aggregate the standard MSA-level housing construction elasticity estimates from Saiz (2010) at the US-state level using MSA area weights. For the Eurozone, I use housing construction elasticity estimates from Cavalleri et al. (2019). These availability of these estimates restricts my main Eurozone sample to Austria, Belgium, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, and the 16 German states. For robustness, I also estimate a specification with all Eurozone countries, without the housing construction elasticity control.

8 Empirical results

Figure 8 shows the local projections results. I scale the coefficients $\beta_h^{(3)}$ of the interactions between shocks and spatial measures by the interquartile ranges of the spatial measures, such that I can compare the effects of monetary policy shocks between two regions with an empirically typical difference in a spatial measure. I report these differences between high-concentration and low-concentration regional responses in relation to average regional responses.

Empirical dampening effects. First, consider residential centralization. Relative to average regional responses, the differences between high-centralization and low-centralization responses reach up to 30% for the United States (in the 1st calendar quarter after the shock) and up to 40% for the Eurozone (on impact). On average until 6 calendar quarters after the shock, the differences amount to 16% for the United States and to 29% the Eurozone. Next, consider residential clustering. Relative to average regional responses, the differences between high-clustering and low-clustering responses reach up to 44% for the United States and up to 59% for the Eurozone (in the 6th calendar quarter after the shock for both). On average, the differences amount to 22% for the United States and to 44% for the Eurozone.

Figure 8: The dampening effect is validated with both spatial measures



Notes: The blue lines show the average regional responses to a monetary policy shock. The orange / brown lines show the interaction coefficients between the shocks and residential centralization or clustering, scaled by the interquartile range of the respective spatial measure. The estimation for the US uses data from contiguous US states except for New Hampshire; the estimation for the Eurozone uses data from Austria, Belgium, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, and the 16 German states.

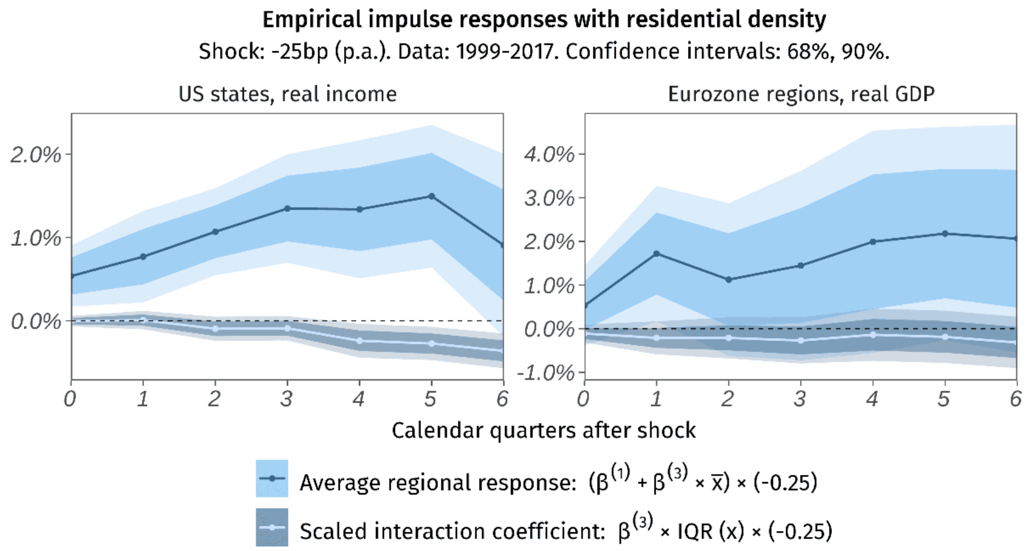
Reasoning about differences in the magnitude of dampening effects between the two currency areas is speculative, especially given the noise associated with effects of monetary policy shocks. A plausible reason for weaker effects in the United States is that city centers can be significantly poorer than suburbs, weakening the association between centrality and housing prices, which is typically not the case in the Eurozone (see, for example, Deffebach et al., 2025). The apparent measurement error in the centralization measure for the United States is consistent with this explanation and could itself further attenuate the estimates.

Comparison between model and empirics. Note that the empirical estimation with centralization and clustering in separate specifications is not directly comparable to the model decomposition analysis. In the decomposition analysis, I isolate the effects of one spatial channel at a time; in reality, both spatial channels are part of the underlying data-generating process. In principle, one should expect that the empirical effects using the spatial measure that is associated with the stronger spatial channel are stronger as well. However, the interaction coefficients are scaled by the interquartile ranges of the respective variable, such that a direct comparison between responses is not possible: The empirical variation in a variable determines the scaling.

Nevertheless, from the results displayed in Figure 8, I can construct responses for "high-concentration" and "low-concentration" regions (following the model exercise), by adding or subtracting the scaled interaction coefficients, divided by 2, to or from the average regional responses. The empirical results yield relative dampening magnitudes between "high-concentration" and "low-concentration" regions of around 20% for centralization and 27% for clustering, averaged over the results for the United States and the Eurozone.

Note that the model decomposition exercise is different from the empirical exercise in terms of what "high" and "low" residential concentration represent; equilibrium consumption equals equilibrium income and GDP in the model but not in the data; the model features real rate shocks while the empirics feature nominal rate shocks; and the empirical exercise might still be subject to omitted variable bias.

Figure 9: A naive density measure performs poorly, consistent with the model



Notes: The dark blue lines show the average regional responses to a monetary policy shock. The light blue lines show the interaction coefficients between the shocks and residential density (given by the total housing volume in a region divided by the area of that region), scaled by the interquartile range of residential density. The estimation for the US uses data from contiguous US states except for New Hampshire; the estimation for the Eurozone uses data from Austria, Belgium, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, and the 16 German states.

Naive residential density. An additional model result is that a naive measure of residential density is not a particularly good predictor of regional differences in the effects of monetary policy shocks: Recall the comparison of Region 2 with Region 3 in the model. This is confirmed in the data, as documented in Figure 9. When estimating the same local projections as before with residential density as the spatial measure, the interaction coefficients are mostly close to zero.

Robustness checks. The robustness checks mentioned throughout Section 7 are documented in Appendix B4. The residential clustering windows do not substantially affect the results; the results hold for regional subsamples and for the full Eurozone sample without the housing construction elasticity control; the US results hold when deflating with the Consumer Price Index excluding shelter and also when using nominal income; the results hold with expansionary and contractionary shocks, as well as with the alternative shock series from Jarociński and Karadi (2020); the results hold when varying the number of lags; and the results are robust to excluding groups of control variables one at a time. Measures based on built-up surface perform worse than measures based on built-up volume, highlighting the relevance of building heights for spatial structure (see, for example, Ahlfeldt et al., 2025).

The same robustness checks (where applicable) for residential density confirm the null result, even when using an "effective" density measure for which I only take into account the built-up area of a region rather than the total area. Importantly, the results for centralization and clustering are barely affected when controlling for the naive measure of density, which confirms my evaluation of the results from the model version without spatial structure as "unrealistic". Recall that this model version predicts identical responses for regions with identical naive density.

Consumption responses. Lastly, annual US-state-level consumption responses display the same patterns as the quarterly income responses, as documented in Appendix B5. Consumption of goods plus non-housing services is stimulated less by monetary policy in regions with higher centralization or clustering. Impulse responses of rental housing services become markedly more positive. This echoes the rental housing demand responses in high-density urban centers from the model (recall Figure 4), providing further support for the model results.

9 Conclusions

This paper investigated whether the spatial structure of housing matters for monetary policy transmission. In the theoretical part of the paper, I developed a monetary business cycle model with spatial structure. In my model, households' location preferences and residential externalities dampen consumption responses to monetary policy shocks in regions whose spatial structures exhibit high levels of *residential concentration*. The dampening effect mainly originates from high-density urban centers, and location preferences are its primary driver. In the empirical part of the paper, I measured residential concentration using geospatial data based on satellite imagery and empirically validated the dampening effect predicted by the model. My findings can inform policymakers on spatial heterogeneity in the effects of interest rate changes. Residential concentration reflects economic mechanisms shaping monetary policy transmission and provides a measurable link between spatial structure and macroeconomic dynamics.

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Appendix A1: Overview of spatial terminology

Spatial concepts, as they are used in this paper.

Location: A fixed land area. Multiple locations constitute a region.

→ Used in the model and in the empirics.
→ In the empirics, a location is a grid cell.

Centrality: Refers to a location's proximity to an (or the nearest) urban center, where an urban center is a selected location or set of locations.

→ Used in the model and in the empirics.

Location preferences: Households derive higher utility from a given unit of housing in locations with higher centrality. In contrast to classic location theory, where centrality matters indirectly through travel costs (see Alonso, 1964), this paper introduces centrality directly into the utility function for simplicity.

→ Used in the model.

Residential centralization: Measures the average centrality in a region, weighted by locations' residential built-up volume.

→ Used in the empirics, and in the model for illustration.
→ Links model and empirics by reflecting the average utility from a given unit of housing.

Residential density: Refers to a location's residential built-up volume per unit of land area.

→ Used in the model and in the empirics.

Residential externalities: Households benefit from local spillovers in housing service flows from living near other households. These spillovers increase with residential density. Residential externalities describe the amenity value that households derive from the locations in which they live, in addition to the value that they derive from their occupied residential built-up volume (see Rossi-Hansberg et al., 2010).

→ Used in the model.

Residential clustering: Measures the average residential density in a region, weighted by locations' residential built-up volume.

→ Used in the empirics, and in the model for illustration.
→ Links model and empirics by reflecting the average level of residential externalities.

Residential concentration: Overarching concept for residential centralization and residential clustering. Describes the degree to which housing volume is spatially grouped. Centralization constitutes a more coarse form of concentration (center vs. periphery / rural areas), clustering constitutes a more localized form (neighborhood-level); see Anas et al. (1998).

Appendix A2: Derivations of households' first-order conditions

Savers. In time period t with following periods $t+k$, $k=0,1,\ldots$, a saver household in location n solves:

$$\max_{\left\{C^{\mathcal{S}}_{t+k,n}, V^{\mathcal{S},\mathcal{O}}_{t+k,n}, V^{\mathcal{S},\mathcal{R}}_{t+k,n}, L^{\mathcal{S}}_{t+k,n}, B^{\mathcal{S}}_{t+k,n}\right\}_{k=0}^{\infty}} \mathbb{E}_t\left[\sum_{k=0}^{\infty}\left(\beta^{\mathcal{S}}\right)^k\left(\log\left(C^{\mathcal{S}}_{t+k,n}\right)+\omega_n\log\left(H^{\mathcal{S}}_{t+k,n}\right)-\left(L^{\mathcal{S}}_{t+k,n}\right)^{\delta}/\delta\right)\right] \tag{A.1}$$

with $H^{\mathcal{S}}_{t+k,n}=V^{\mathcal{S},\mathcal{O}}_{t+k,n}+\xi V_n$, subject to the budget constraint

$$\begin{aligned} &C^{\mathcal{S}}_{t+k,n}+P_{t+k,n}\left(V^{\mathcal{S},\mathcal{O}}_{t+k,n}-V^{\mathcal{S},\mathcal{O}}_{t+k-1,n}+V^{\mathcal{S},\mathcal{R}}_{t+k,n}-V^{\mathcal{S},\mathcal{R}}_{t+k-1,n}\right)+R_{t+k-1}B^{\mathcal{S}}_{t+k-1,n} \\ &\quad = W^{\mathcal{S}}_{t+k}L^{\mathcal{S}}_{t+k,n}+Q_{t+k}V^{\mathcal{S},\mathcal{R}}_{t+k,n}+B^{\mathcal{S}}_{t+k,n}, \end{aligned} \tag{A.2}$$

the borrowing constraint $B^{\mathcal{S}}_{t+k,n}\leq\gamma P_{t+k,n}V^{\mathcal{S},\mathcal{O}}_{t+k,n}$ which never binds in equilibrium, and the transversality condition $\lim_{k\to\infty}\mathbb{E}_t\left[(C^{\mathcal{S}}_{t+k,n})^{-1}A^{\mathcal{S}}_{t+k,n}\right]=0$, given V_n, initial values $V^{\mathcal{S},\mathcal{O}}_{t-1,n}$, $V^{\mathcal{S},\mathcal{R}}_{t-1,n}$, $B^{\mathcal{S}}_{t-1,n}$, and prices $P_{t,n}$, $Q_{t,n}$, $W^{\mathcal{S}}_t$, and R_{t-1}. Denoting $A^{\mathcal{S}}_{t+k,n}=-B^{\mathcal{S}}_{t+k,n}$, the saver households' Lagrangian is

$$\begin{aligned} \mathcal{L}^{\mathcal{S}}_{t,n}=\mathbb{E}_t\Bigg[&\sum_{k=0}^{\infty}\left(\beta^{\mathcal{S}}\right)^k\left(\log\left(C^{\mathcal{S}}_{t+k,n}\right)+\omega_n\log\left(V^{\mathcal{S},\mathcal{O}}_{t+k,n}+\xi V_n\right)-\left(L^{\mathcal{S}}_{t+k,n}\right)^{\delta}/\delta\right) \\ &+Z^{\mathcal{S}}_{t+k,n}\Big(W^{\mathcal{S}}_{t+k}L^{\mathcal{S}}_{t+k,n}+Q_{t+k}V^{\mathcal{S},\mathcal{R}}_{t+k,n}+R_{t+k-1}A^{\mathcal{S}}_{t+k-1,n} \\ &\quad -C^{\mathcal{S}}_{t+k,n}-P_{t+k,n}\left(V^{\mathcal{S},\mathcal{O}}_{t+k,n}-V^{\mathcal{S},\mathcal{O}}_{t+k-1,n}+V^{\mathcal{S},\mathcal{R}}_{t+k,n}-V^{\mathcal{S},\mathcal{R}}_{t+k-1,n}\right)-A^{\mathcal{S}}_{t+k,n}\Big)\Bigg] \end{aligned} \tag{A.3}$$

with the budget constraint multiplier $Z^{\mathcal{S}}_{t+k,n}$. The first-order conditions are

$$\frac{\partial\mathcal{L}^{\mathcal{S}}_{t,n}}{\partial C^{\mathcal{S}}_{t+k,n}}=\mathbb{E}_t\left[\left(\beta^{\mathcal{S}}\right)^k\left(C^{\mathcal{S}}_{t+k,n}\right)^{-1}-Z^{\mathcal{S}}_{t+k,n}\right]=0, \tag{A.4}$$

$$\frac{\partial\mathcal{L}^{\mathcal{S}}_{t,n}}{\partial V^{\mathcal{S},\mathcal{O}}_{t+k,n}}=\mathbb{E}_t\left[\left(\beta^{\mathcal{S}}\right)^k\omega_n\left(V^{\mathcal{S},\mathcal{O}}_{t+k,n}+\xi V_n\right)^{-1}-Z^{\mathcal{S}}_{t+k,n}P_{t+k,n}+Z^{\mathcal{S}}_{t+k+1,n}P_{t+k+1,n}\right]=0, \tag{A.5}$$

$$\frac{\partial\mathcal{L}^{\mathcal{S}}_{t,n}}{\partial V^{\mathcal{S},\mathcal{R}}_{t+k,n}}=\mathbb{E}_t\left[Z^{\mathcal{S}}_{t+k,n}Q_{t+k,n}-Z^{\mathcal{S}}_{t+k,n}P_{t+k,n}+Z^{\mathcal{S}}_{t+k+1,n}P_{t+k+1,n}\right]=0, \tag{A.6}$$

$$\frac{\partial\mathcal{L}^{\mathcal{S}}_{t,n}}{\partial L^{\mathcal{S}}_{t+k,n}}=\mathbb{E}_t\left[-\left(\beta^{\mathcal{S}}\right)^k\left(L^{\mathcal{S}}_{t+k,n}\right)^{\delta-1}+Z_{t+k,n}W^{\mathcal{S}}_{t+k}\right]=0, \tag{A.7}$$

$$\frac{\partial\mathcal{L}^{\mathcal{S}}_{t,n}}{\partial A^{\mathcal{S}}_{t+k,n}}=\mathbb{E}_t\left[-Z_{t+k,n}+Z_{t+k+1,n}R_{t+k}\right]=0. \tag{A.8}$$

Setting $k=0$ and replacing $V^{\mathcal{S},\mathcal{O}}_{t,n}+\xi V_n=H^{\mathcal{S}}_{t,n}$ as well as the multipliers using (A.4) yields the equations from the main text.

Borrowers. A borrower household solves:

$$\max_{\left\{C^{\mathcal{B}}_{t+k,n},V^{\mathcal{B},\mathcal{O}}_{t+k,n},V^{\mathcal{B},\mathcal{R}}_{t+k,n},L^{\mathcal{B}}_{t+k,n},B^{\mathcal{B}}_{t+k,n}\right\}_{k=0}^{\infty}} \mathbb{E}_t\left[\sum_{k=0}^{\infty}(\beta^{\mathcal{B}})^k\left(\log(C^{\mathcal{B}}_{t+k,n})+\omega_n\log(H^{\mathcal{B}}_{t+k,n})-(L^{\mathcal{B}}_{t+k,n})^{\delta}/\delta\right)\right] \tag{A.9}$$

with $H^{\mathcal{B}}_{t+k,n}=\left(\phi^{\mathcal{O}}(V^{\mathcal{B},\mathcal{O}}_{t+k,n})^{1-\eta}+\phi^{\mathcal{R}}(V^{\mathcal{B},\mathcal{R}}_{t+k,n})^{1-\eta}\right)^{1/(1-\eta)}+\xi V_n$, subject to the budget constraint

$$\begin{aligned}&C^{\mathcal{B}}_{t+k,n}+P_{t+k,n}(V^{\mathcal{B},\mathcal{O}}_{t+k,n}-V^{\mathcal{B},\mathcal{O}}_{t+k-1,n})+R_{t+k-1}B^{\mathcal{B}}_{t+k-1,n}+Q_{t+k}V^{\mathcal{B},\mathcal{R}}_{t+k,n}\\&\quad=W^{\mathcal{B}}_{t+k}L^{\mathcal{B}}_{t+k,n}+B^{\mathcal{B}}_{t+k,n}\end{aligned} \tag{A.10}$$

and the borrowing constraint $B^{\mathcal{B}}_{t+k,n}\leq\gamma P_{t+k,n}V^{\mathcal{B},\mathcal{O}}_{t+k,n}$ which always binds in equilibrium, given V_n, initial values $V^{\mathcal{B},\mathcal{O}}_{t-1,n}$ and $B^{\mathcal{B}}_{t-1,n}$, and prices $P_{t,n}$, $Q_{t,n}$, $W^{\mathcal{B}}_t$, and R_{t-1}. As $B^{\mathcal{B}}_{t+k,n}=\gamma P_{t+k,n}V^{\mathcal{B},\mathcal{O}}_{t+k,n}$, the choice variable $B^{\mathcal{B}}_{t+k,n}$ becomes implicit within the decision problem and can be replaced. The borrower households' Lagrangian is

$$\begin{aligned}\mathcal{L}^{\mathcal{B}}_{t,n}=\mathbb{E}_t\Bigg[&\sum_{k=0}^{\infty}(\beta^{\mathcal{B}})^k\left(\log(C^{\mathcal{B}}_{t+k,n})+\omega_n\log(V^{\mathcal{B}}_{t+k,n}+\xi V_n)-(L^{\mathcal{B}}_{t+k,n})^{\delta}/\delta\right)\\&+Z^{\mathcal{B}}_{t+k,n}\Big(W^{\mathcal{B}}_{t+k}L^{\mathcal{B}}_{t+k,n}-C^{\mathcal{B}}_{t+k,n}-P_{t+k,n}((1-\gamma)V^{\mathcal{B},\mathcal{O}}_{t+k,n}-V^{\mathcal{B},\mathcal{O}}_{t+k-1,n})\\&\quad-R_{t+k-1}\gamma P_{t+k-1,n}V^{\mathcal{B},\mathcal{O}}_{t+k-1,n}-Q_{t+k}V^{\mathcal{B},\mathcal{R}}_{t+k,n}\Big)\Bigg]\end{aligned} \tag{A.11}$$

with the budget constraint multiplier $Z^{\mathcal{B}}_{t+k,n}$, denoting

$$V^{\mathcal{B}}_{t+k,n}=\left(\phi^{\mathcal{O}}(V^{\mathcal{B},\mathcal{O}}_{t+k,n})^{1-\eta}+\phi^{\mathcal{R}}(V^{\mathcal{B},\mathcal{R}}_{t+k,n})^{1-\eta}\right)^{1/(1-\eta)}. \tag{A.12}$$

The first-order conditions are

$$\frac{\partial\mathcal{L}^{\mathcal{B}}_{t,n}}{\partial C^{\mathcal{B}}_{t+k,n}}=\mathbb{E}_t\left[(\beta^{\mathcal{B}})^k(C^{\mathcal{B}}_{t+k,n})^{-1}-Z^{\mathcal{B}}_{t+k,n}\right]=0, \tag{A.13}$$

$$\begin{aligned}\frac{\partial\mathcal{L}^{\mathcal{B}}_{t,n}}{\partial V^{\mathcal{B},\mathcal{O}}_{t+k,n}}=\mathbb{E}_t\Big[&(\beta^{\mathcal{B}})^k\omega_n(V^{\mathcal{B}}_{t+k,n}+\xi V_n)^{-1}\phi^{\mathcal{O}}(V^{\mathcal{B}}_{t+k,n})^{\eta}(V^{\mathcal{B},\mathcal{O}}_{t+k,n})^{-\eta}\\&-Z^{\mathcal{B}}_{t+k,n}P_{t+k,n}(1-\gamma)+Z^{\mathcal{B}}_{t+k+1,n}P_{t+k+1,n}-Z^{\mathcal{B}}_{t+k+1,n}R_{t+k}\gamma P_{t+k}\Big]=0,\end{aligned} \tag{A.14}$$

$$\frac{\partial\mathcal{L}^{\mathcal{B}}_{t,n}}{\partial V^{\mathcal{B},\mathcal{R}}_{t+k,n}}=\mathbb{E}_t\left[(\beta^{\mathcal{B}})^k\omega_n(V^{\mathcal{B}}_{t+k,n}+\xi V_n)^{-1}\phi^{\mathcal{R}}(V^{\mathcal{B}}_{t+k,n})^{\eta}(V^{\mathcal{B},\mathcal{R}}_{t+k,n})^{-\eta}-Z^{\mathcal{B}}_{t+k,n}Q_{t+k,n}\right]=0, \tag{A.15}$$

$$\frac{\partial\mathcal{L}^{\mathcal{B}}_{t,n}}{\partial L^{\mathcal{B}}_{t+k,n}}=\mathbb{E}_t\left[-(\beta^{\mathcal{B}})^k(L^{\mathcal{B}}_{t+k,n})^{\delta-1}+Z_{t+k,n}W^{\mathcal{B}}_{t+k}\right]=0. \tag{A.16}$$

Setting $k=0$ and replacing $V^{\mathcal{B}}_{t,n}+\xi V_n=H^{\mathcal{B}}_{t,n}$ as well as the multipliers using (A.13) yields the equations from the main text.

Appendix A3: Log-linearized model

The following equations provide the log-linearized model and thus describe a first-order approximation of the model's behavior around the non-stochastic steady-state. Omissions of time indices denote steady-state values; hats denote percent deviations from steady-state values.

$$C_n^{\mathcal{S}}\widehat{C}_{t,n}^{\mathcal{S}} + P_n V_n^{\mathcal{S},\mathcal{O}}\big(\widehat{V}_{t,n}^{\mathcal{S},\mathcal{O}} - \widehat{V}_{t-1,n}^{\mathcal{S},\mathcal{O}}\big) + P_n V_n^{\mathcal{S},\mathcal{R}}\big(\widehat{V}_{t,n}^{\mathcal{S},\mathcal{R}} - \widehat{V}_{t-1,n}^{\mathcal{S},\mathcal{R}}\big) + A_n^{\mathcal{S}}\widehat{A}_{t,n}^{\mathcal{S}}$$
$$= W^{\mathcal{S}} L_n^{\mathcal{S}}\big(\widehat{W}_t^{\mathcal{S}} + \widehat{L}_{t,n}^{\mathcal{S}}\big) + Q_n V_n^{\mathcal{S},\mathcal{R}}\big(\widehat{Q}_{t,n} + \widehat{V}_{t,n}^{\mathcal{S},\mathcal{R}}\big) + R A_n^{\mathcal{S}}\big(\widehat{R}_{t-1} + \widehat{A}_{t-1,n}^{\mathcal{S}}\big)$$
(A.17: Savers' budget constraint)

$$\widehat{P}_{t,n} - \widehat{C}_{t,n}^{\mathcal{S}} = -\big(1-\beta^{\mathcal{S}}\big)\big(V_n^{\mathcal{S},\mathcal{O}}/H_n^{\mathcal{S}}\big)\widehat{V}_{t,n}^{\mathcal{S},\mathcal{O}} + \beta^{\mathcal{S}}\mathbb{E}_t\big[\widehat{P}_{t+1,n} - \widehat{C}_{t+1,n}^{\mathcal{S}}\big]$$
(A.18: Savers' owner-occupied housing demand)

$$P_n\widehat{P}_{t,n} - Q_n\widehat{Q}_{t,n} - \big(P_n - Q_n\big)\widehat{C}_{t,n}^{\mathcal{S}} = \beta^{\mathcal{S}} P_n\mathbb{E}_t\big[\widehat{P}_{t+1,n} - \widehat{C}_{t+1,n}^{\mathcal{S}}\big] \quad \text{(A.19: Rental housing supply)}$$

$$\big(\delta-1\big)\widehat{L}_{t,n}^{\mathcal{S}} = \widehat{W}_t^{\mathcal{S}} - \widehat{C}_{t,n}^{\mathcal{S}} \quad \text{(A.20: Savers' labor supply)}$$

$$-\widehat{C}_{t,n}^{\mathcal{S}} = \widehat{R}_t + \mathbb{E}_t\big[-\widehat{C}_{t+1,n}^{\mathcal{S}}\big] \quad \text{(A.21: Euler equation)}$$

$$C_n^{\mathcal{B}}\widehat{C}_{t,n}^{\mathcal{B}} + P_n V_n^{\mathcal{B},\mathcal{O}}\big((1-\gamma)\widehat{V}_{t,n}^{\mathcal{B},\mathcal{O}} - \widehat{V}_{t-1,n}^{\mathcal{B},\mathcal{O}} - \gamma\widehat{P}_{t,n}\big) + R\gamma P_n V_n^{\mathcal{B},\mathcal{O}}\big(\widehat{R}_{t-1} + \widehat{P}_{t-1,n} + \widehat{V}_{t-1,n}^{\mathcal{B},\mathcal{O}}\big)$$
$$+ Q_n V_n^{\mathcal{B},\mathcal{R}}\big(\widehat{Q}_{t,n} + \widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}}\big) = W^{\mathcal{B}} L_n^{\mathcal{B}}\big(\widehat{W}_t^{\mathcal{B}} + \widehat{L}_{t,n}^{\mathcal{B}}\big) \quad \text{(A.22: Borrowers' budget constraint)}$$

$$(1-\gamma)\big(\widehat{P}_{t,n} - \widehat{C}_{t,n}^{\mathcal{B}}\big) + \beta^{\mathcal{B}} R\gamma\big(\widehat{R}_t + \widehat{P}_{t,n} + \mathbb{E}_t\big[-\widehat{C}_{t+1,n}^{\mathcal{B}}\big]\big) = \beta^{\mathcal{B}}\mathbb{E}_t\big[\widehat{P}_{t+1,n} - \widehat{C}_{t+1,n}^{\mathcal{B}}\big]$$
$$+ \big(1-\gamma+\beta^{\mathcal{B}}(R\gamma-1)\big)\Big(\Big(-\phi^{\mathcal{O}}\big(V_n^{\mathcal{B},\mathcal{O}}/H_n^{\mathcal{B}}\big)\big(V_n^{\mathcal{B},\mathcal{O}}/V_n^{\mathcal{B}}\big)^{-\eta} + \eta\phi^{\mathcal{O}}\big(V_n^{\mathcal{B},\mathcal{O}}/V_n^{\mathcal{B}}\big)^{1-\eta} - \eta\Big)\widehat{V}_{t,n}^{\mathcal{B},\mathcal{O}}$$
$$+ \Big(-\phi^{\mathcal{R}}\big(V_n^{\mathcal{B},\mathcal{R}}/H_n^{\mathcal{B}}\big)\big(V_n^{\mathcal{B},\mathcal{R}}/V_n^{\mathcal{B}}\big)^{-\eta} + \eta\phi^{\mathcal{R}}\big(V_n^{\mathcal{B},\mathcal{R}}/V_n^{\mathcal{B}}\big)^{1-\eta}\Big)\widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}}\Big)$$
(A.23: Borrowers' owner-occupied housing demand)

$$\widehat{Q}_{t,n} - \widehat{C}_{t,n}^{\mathcal{B}} = \Big(-\phi^{\mathcal{R}}\big(V_n^{\mathcal{B},\mathcal{R}}/H_n^{\mathcal{B}}\big)\big(V_n^{\mathcal{B},\mathcal{R}}/V_n^{\mathcal{B}}\big)^{-\eta} + \eta\phi^{\mathcal{R}}\big(V_n^{\mathcal{B},\mathcal{R}}/V_n^{\mathcal{B}}\big)^{1-\eta} - \eta\Big)\widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}}$$
$$+ \Big(-\phi^{\mathcal{O}}\big(V_n^{\mathcal{B},\mathcal{O}}/H_n^{\mathcal{B}}\big)\big(V_n^{\mathcal{B},\mathcal{O}}/V_n^{\mathcal{B}}\big)^{-\eta} + \eta\phi^{\mathcal{O}}\big(V_n^{\mathcal{B},\mathcal{O}}/V_n^{\mathcal{B}}\big)^{1-\eta}\Big)\widehat{V}_{t,n}^{\mathcal{B},\mathcal{O}}$$
(A.24: Rental housing demand)

$$\big(\delta-1\big)\widehat{L}_{t,n}^{\mathcal{B}} = \widehat{W}_t^{\mathcal{B}} - \widehat{C}_{t,n}^{\mathcal{B}} \quad \text{(A.25: Borrowers' labor supply)}$$

$$\widehat{Y}_t = \alpha^{\mathcal{S}}\widehat{L}_t^{\mathcal{S},\mathcal{F}} + \alpha^{\mathcal{B}}\widehat{L}_t^{\mathcal{B},\mathcal{F}} \quad \text{(A.26: Production)}$$

$$\widehat{Y}_t - \widehat{L}_t^{\mathcal{T},\mathcal{F}} = \widehat{W}_t^{\mathcal{T}} \text{ for } \mathcal{T} \in \{\mathcal{S},\mathcal{B}\} \quad \text{(A.27: Labor demand)}$$

$$\widehat{R}_t = \rho\widehat{R}_{t-1} + \widehat{E}_t \quad \text{(A.28: Monetary policy)}$$

$$Y\widehat{Y}_t = \textstyle\sum_{n=1}^{N}\mu_n^{\mathcal{S}} V_n C_n^{\mathcal{S}}\widehat{C}_{t,n}^{\mathcal{S}} + \sum_{n=1}^{N}\mu_n^{\mathcal{B}} V_n C_n^{\mathcal{B}}\widehat{C}_{t,n}^{\mathcal{B}} \quad \text{(A.29: Goods market clearing)}$$

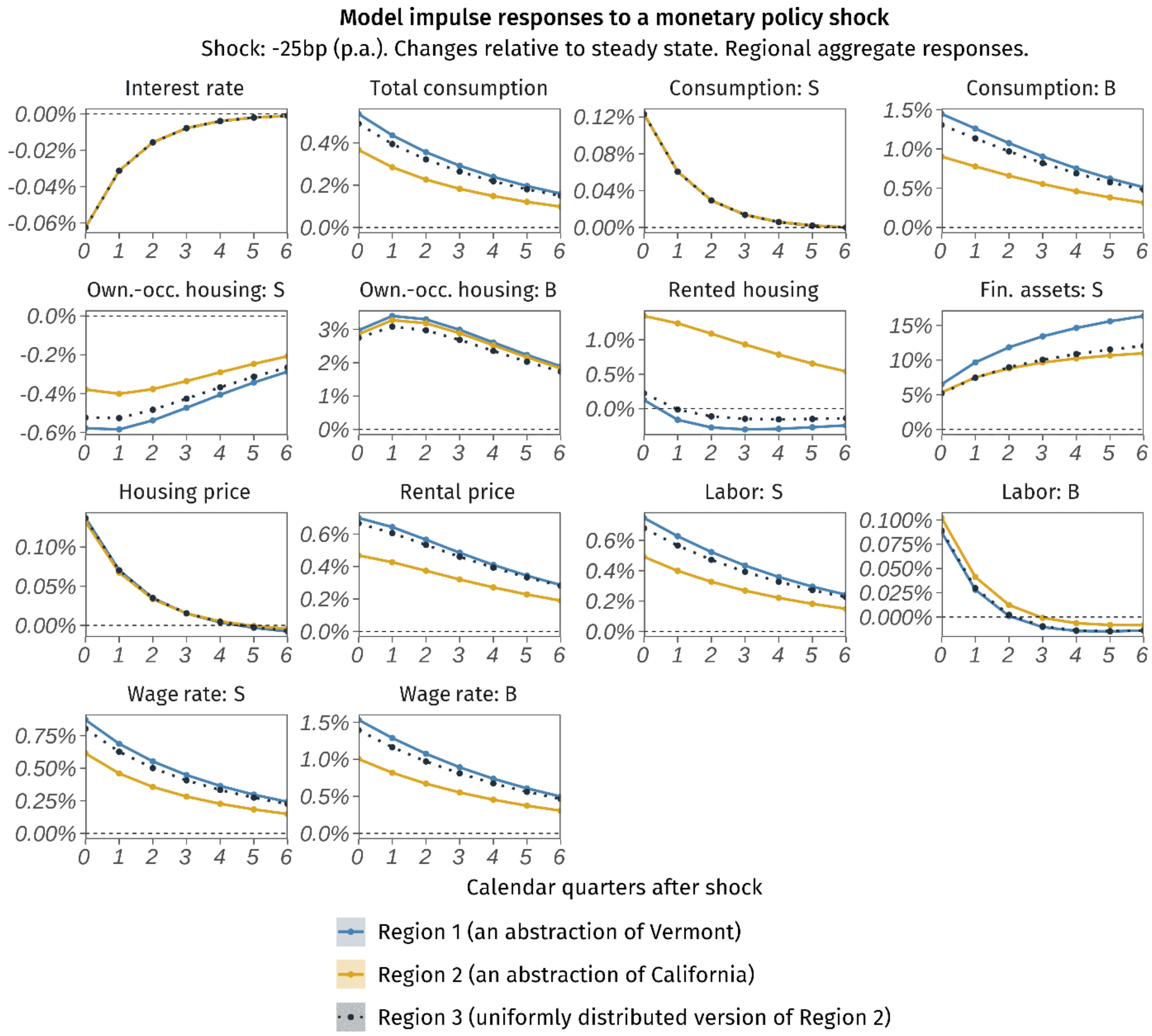
$$L^{\mathcal{T},\mathcal{F}}\widehat{L}_t^{\mathcal{T},\mathcal{F}} = \textstyle\sum_{n=1}^{N}\mu_n^{\mathcal{T}} V_n L_n^{\mathcal{T}}\widehat{L}_{t,n}^{\mathcal{T}} \text{ for } \mathcal{T} \in \{\mathcal{S},\mathcal{B}\} \quad \text{(A.30: Labor market clearing)}$$

$$\mu_n^{\mathcal{S}} V_n V_n^{\mathcal{S},\mathcal{O}}\widehat{V}_{t,n}^{\mathcal{S},\mathcal{O}} + \mu_n^{\mathcal{B}} V_n V_n^{\mathcal{B},\mathcal{O}}\widehat{V}_{t,n}^{\mathcal{B},\mathcal{O}} + \mu_n^{\mathcal{B}} V_n V_n^{\mathcal{B},\mathcal{R}}\widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}} = 0 \quad \text{(A.31: Housing market clearing)}$$

$$\widehat{V}_{t,n}^{\mathcal{B},\mathcal{R}} = \widehat{V}_{t,n}^{\mathcal{S},\mathcal{R}} \quad \text{(A.32: Rental market clearing)}$$

Appendix A4: Regional baseline model impulse responses

Figure A.1: Impulse responses of all regional variables from the baseline model



Notes: Residential concentration is low in Region 1, high in Region 2, and medium in Region 3. "S" refers to savers, "B" refers to borrowers. Where applicable, the image shows per-capita responses.

Intuitions. The following explanations may help in understanding the impulse responses:

(1) In general, in response to the interest rate decrease, borrowers' consumption increases strongly as explained in Section 3, while their labor supply responds only weakly due to a wealth effect from decreased debt service costs. This puts upward pressure on borrowers' wages relative to those of savers. As a result, firms substitute toward the savers' labor. Overall, the realized labor response of savers is strongly positive, while the realized labor response of borrowers is around zero and becomes weakly negative after 3 calendar quarters.

(2) Savers sell housing to borrowers, but do not consume more from the proceeds of sale: With the real rate quickly returning to its steady-state level, the Euler equation brings the savers' consumption back toward steady state. The unexpected housing sale proceeds accumulate in financial assets – an unrealistic model feature, and a downside of the lack of financial market clearing. This is not a problem here because savers' consumption responses do not matter for my main results. The asset drift is to be interpreted as a change in net foreign assets.

(3) The response of housing purchase prices is unrealistically small, a typical weakness for this model class in which housing is priced by the savers' consumption, as savers are the only unconstrained agents in the model and can arbitrage across assets. This weakness does not cause a concern in this case, as price responses do not matter for my main results.

(4) Rental prices are not directly tied to savers' consumption, as they are determined in a spot market that clears each period, and therefore respond more strongly than purchase prices. Nonetheless, rental prices are affected by expected capital gains via the savers' rental supply first-order condition.

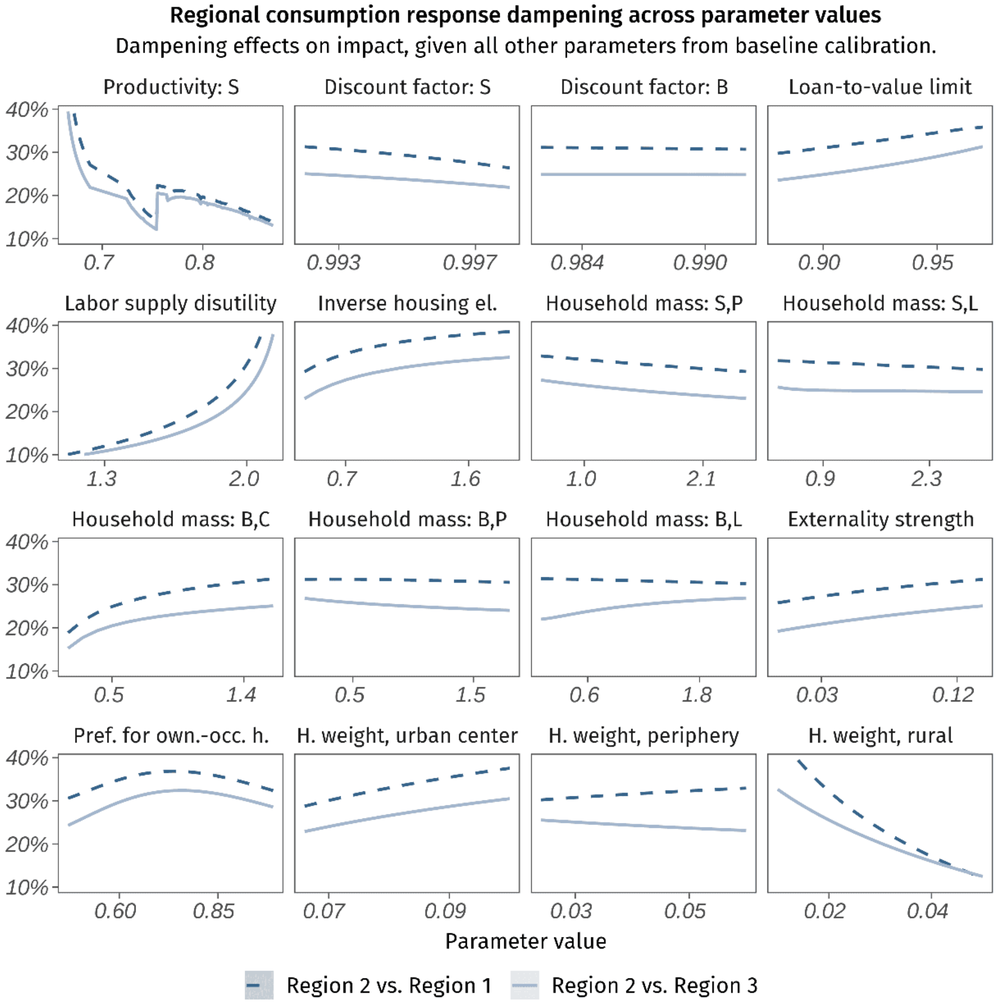
(5) Rental price responses are relatively weak in the high-concentration Region 2. This is driven by strongly increased rental supply in urban center locations: High rental price levels in urban centers imply large potential capital gains from supplying rental housing. Consequently, rental prices in urban center locations experience weaker upward pressure, while rented housing quantities experience stronger upward pressure.

Borrowers in the urban center locations of Region 2 go along with this strong increase in rented housing quantities due to the strong residential externalities in the urban center locations of Region 2 (which render their rental housing demand responses more positive, as explained in Section 3). In the urban center locations of Region 3, residential externalities are relatively weak, such that this effect does not materialize. There are no urban center locations in Region 1.

(6) The borrowers' region-wide owner-occupied housing responses are roughly identical across regions, but this is in fact coincidental. What matters for my main results is heterogeneity in location-specific owner-occupied housing responses. As discussed in Section 5, these are strongly positive in the urban center locations of the high-concentration Region 2 compared to all other locations in all regions.

Appendix A5: Sensitivity analysis of the model results

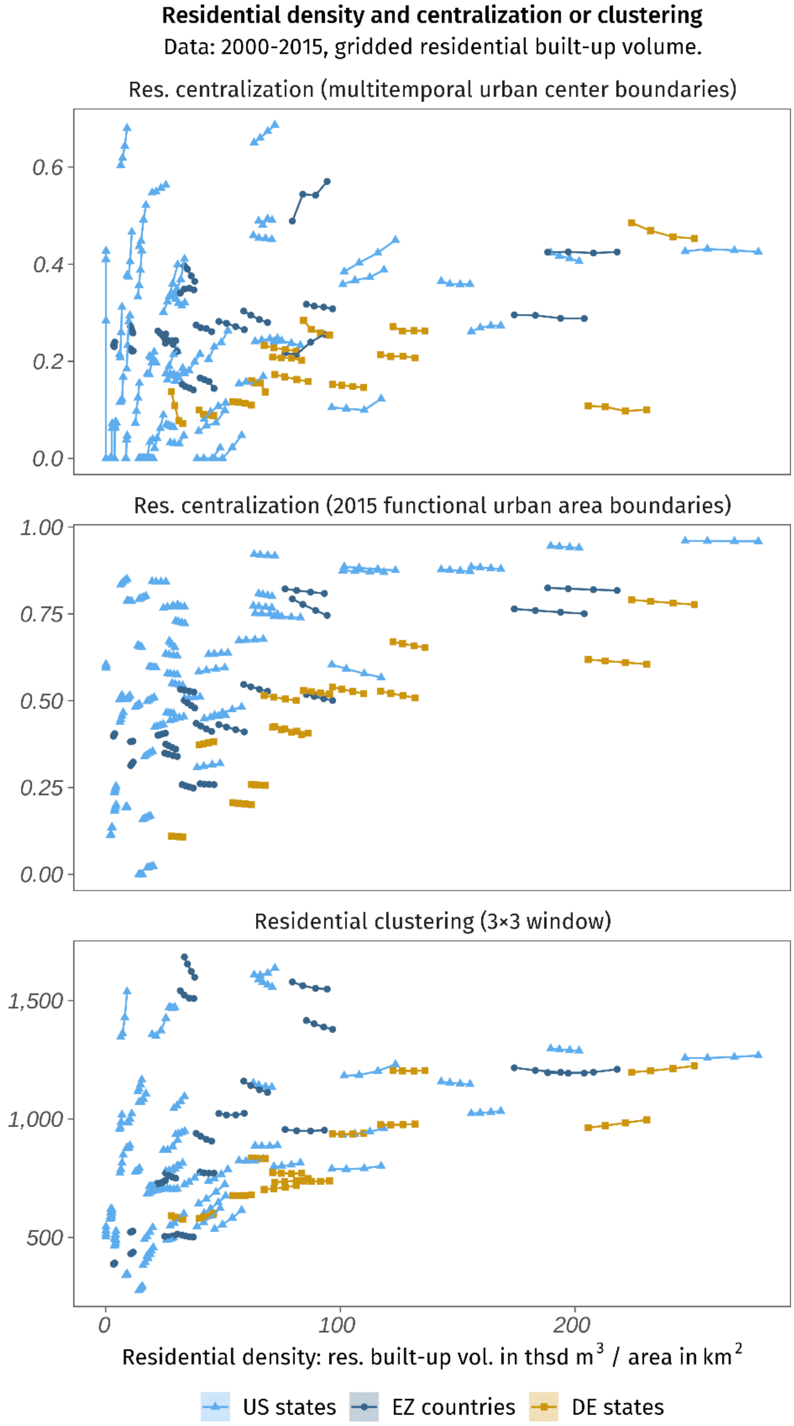
Figure A.2: The dampening effect holds for wide ranges of parameter values



Notes: Displayed are impact responses (that is, the responses in the calendar quarter in which the shock occurs) of regional consumption in Region 2 compared to Regions 1, plotted against parameter values. More precisely, the image shows impact responses in Region 2 divided by impact responses in Region 1 or 3, subtracted from 1, and expressed in percent.
Each data point represents a calibration of the model that starts from the baseline calibration and changes a parameter to the value reported on the horizontal axis.
"S" stands for savers, "B" stands for borrowers, "C" stands for urban center locations, "P" stands for periphery locations, and "L" stands for rural locations.

Appendix B1: Additional descriptive illustrations

Figure B.1: Scatterplots of residential density and centralization or clustering



Notes: The regions displayed are US states (including Alaska, Hawaii, and New Hampshire which are not used in the empirical analysis), Eurozone countries (with members as of 2024, including countries not used in the empirical analysis), and German states. I exclude Malta and the German city-states Berlin, Hamburg, and Bremen from the plot, as these are outliers. The measurements are produced with residential built-up volume (on a 300 m × 300 m grid for clustering and on a 1 km × 1 km grid for centralization) and urbanization categories (for centralization) from the Global Human Settlement Layer database (Melchiorri et al., 2024; Schiavina et al., 2019; Pesaresi and Politis, 2023b), as well as state and country boundaries from the US Census Bureau and GADM.

Appendix B2: Data sources for the empirical analysis

Geospatial data: Global Human Settlement Layer database (European Commission Joint Research Centre, 2023; Pesaresi et al., 2024): built-up volume (GHS-BUILT-V: Pesaresi and Politis, 2023b), built-up surface (GHS-BUILT-S: Pesaresi and Politis, 2023a), urban center boundaries (GHS-UCDB: Melchiorri et al., 2024), and FUA boundaries (GHS-FUA: Schiavina et al., 2019).
US state and MSA shapes from US Census Bureau (tl_2013_us_state, tl_2013_us_cbsa, tl_2013_us_metdiv).
Eurozone shapes from GADM (data by country, level-1 for German states and level-0 for other countries).
Interest rates and shocks: EONIA from the replication files of Gulyas et al. (2024) and shadow rate from the website of Jing Cynthia Wu.
US effective federal funds rate and shadow rate from the Federal Reserve Bank of Atlanta (Wu-Xia series).
Baseline shock series for the US from the website of Thomas Drechsel and GitHub repository of Ralph Luetticke.
Baseline shock series for the Eurozone from the replication files of Gulyas et al. (2024).
Alternative shock series for the US and the Eurozone from the website of Marek Jarociński.
Income, GDP, and GVA: US state-level income from BEA Regional Accounts: state personal income, seasonally adjusted, current dollar prices (SQINC1).
US state-level sectoral income from the same data source (SQINC5S; C: construction, D: manufacturing, 01-02: farm earnings, 07-09: agricultural services, forestry, and fishing; SQINC5N; 23: construction, 31-33: 53: real estate and rental and leasing, manufacturing, 111-112: farm earnings, 113-115: forestry, fishing, and related activities). The SQINC5S dataset and the SQINC5N dataset overlap from 1999 to 2001. Overlapping observations are averaged where possible.
Eurozone-country-level real GDP from Eurostat: seasonally and calendar adjusted, chain linked volumes (namq_10_ndp).
Eurozone-country-level GVA by industry from the same data source (namq_10_a10; total, A: agriculture, forestry and fishing, B-E: industry (except construction), F: construction).
German state-level real GDP: website of Robert Lehmann. This dataset only includes growth rates; levels are backed out by setting a reference period (the first period in the sample, which is arbitrary).
German state-level sectoral GVA from GENESIS (82111-0011; total, WZ08-F: construction, WZ08-C: manufacturing, WZ08-A: agriculture, forestry, and fishing).
Consumer price indices: US national and census-region-level CPI from FRED: quarterly average; seasonally adjusted for the national CPI, not seasonally adjusted for the census-region level CPI (manual adjustment using X-13ARIMA-SEATS); (CPIAUCSL, CUUR0100SA0, CUUR0200SA0, CUUR0300SA0, CUUR0400SA0, CUUR0100SA0L2, CUUR0200SA0L2, CUUR0300SA0L2, CUUR0400SA0L2); primary data source: BLS.
Eurozone-level HICP from ECB Data Portal: working day and seas. adj. (ICP.M.U2.Y.000000.3.INX).
Demographics: US state-level population from FRED (ALPOP, ARPOP, AZPOP, CAPOP, COPOP, CTPOP, DEPOP, FLPOP, GAPOP, IAPOP, IDPOP, ILPOP, INPOP, KSPOP, KYPOP, LAPOP, MAPOP, MDPOP, MEPOP, MIPOP, MNPOP, MOPOP, MSPOP, MTPOP, NCPOP, NDPOP, NEPOP, NJPOP, NMPOP, NVPOP, NYPOP, OHPOP, OKPOP, ORPOP, PAPOP, RIPOP, SCPOP, SDPOP, TNPOP, TXPOP, UTPOP, VAPOP, VTPOP, WAPOP, WIPOP, WVPOP, WYPOP); primary data source: US Census Bureau.
US state-level population by age from US Census Bureau (st-est00int-agesex, sc-est2019-agesex-civ).
Eurozone-country-level population from Eurostat: population on 1 January by broad age group and sex (demo_pjanbroad).
German state-level population from GENESIS: population by age (12411-0012).
Housing construction elasticity: US MSA-level housing construction elasticity: replication files of Aastveit and Anundsen (2022); primary data source: Saiz (2010).
Eurozone country-level housing construction elasticity: Cavalleri et al. (2019), Table B.6.

Appendix B3: Summary statistics for the empirical analysis

Table B.1: Summary statistics of data used in the empirical analysis, United States

Variable	N	Avg	SD	Min	Mdn	Max
State	47	–	–	–	–	–
Calendar quarter	73	–	–	1999 Q2	–	2017 Q2
Res. centralization (urban center) (in %)	2,847	23	18	0	20	69
Res. centralization (FUA) (in %)	2,847	57	26	0	59	96
Res. centr.: 2D (urban center) (in %)	2,847	14	14	0	10	56
Res. clustering (1×1) (in thsd m^3)	2,847	111	38	40	104	207
Res. clustering (3×3) (in thsd m^3)	2,847	848	310	277	794	1,640
Res. clustering (5×5) (in thsd m^3)	2,847	2,126	816	640	2,001	4,237
Res. clustering (7×7) (in thsd m^3)	2,847	3,858	1,547	1,053	3,628	7,891
Res. clustering: 2D (3×3) (in thsd m^2)	2,847	77	31	30	71	168
Res. density (in thsd m^3 / km^2)	2,847	45	51	2	28	279
Res. d.: only built-up area (in thsd m^3 / km^2)	2,847	153	106	40	118	483
Res. density: 2D (in thsd m^2 / km^2)	2,847	9	8	0.5	6	43
Monetary policy shock (baseline, in bp p.a.)	67	0	11	−37	0	29
Monetary policy shock (alternative, in bp p.a.)	67	−2	10	−38	−1	18
Fed funds rate or shadow rate (in % p.a.)	63	1.7	2.8	−2.9	1.4	6.6
National CPI inflation (in %, quarterly)	63	0.6	0.6	−2.3	0.7	1.5
Income (in bn USD, quarterly)	3,431	63	74	3	41	570
Construction sector inc. share (in %)	2,847	4.8	1.1	2.7	4.7	10.8
Manufacturing sector inc. share (in %)	2,847	8.5	3.5	2.1	8.3	21.3
Primary sector inc. share (in %)	2,847	1.4	1.6	0.1	0.9	10.9
Share of population aged $>$ 64 (in %)	2,847	13.2	1.7	8.5	13.2	19.3
Share of population aged $<$ 20 (in %)	2,847	27.3	2.0	21.9	27.2	36.3
Residential built-up volume share (in %)	2,847	84	3	77	84	90
Housing construction elasticity	47	2.45	1.03	0.94	2.22	4.99

Notes: The sample includes the 50 US states except for Alaska, Hawaii, and New Hampshire (that is, all contiguous US states except for New Hampshire) due to missing housing construction elasticity estimates. Out of the potential 2,961 observations for interacted control variables, 114 are dropped from the estimation due to missing sectoral variables. Spatial measurements and demographics are linearly interpolated at the quarterly level.

The beginning of the sample is synchronized to the beginning of the Eurozone sample. Due to using lagged interaction variables and 4 lags of other variables, the (main) estimation starts in 2000 Q2. The end of the sample is 6 calendar quarters (the effect horizon) after the last available monetary policy shock in 2015 Q4. The table reports values that enter the regressions directly, including data for the centralization-based outliers Montana, North Dakota, South Dakota, and Utah (these states are not included in the main specification for centralization due to appearing to be prone to measurement error in terms of centralization; this restriction does not affect specifications with residential clustering).

The baseline monetary policy shocks are from Aruoba and Drechsel (2025) until 2008 Q4 and from Bügel et al. (2024) after 2008 Q4. The alternative monetary policy shocks are from Jarociński and Karadi (2020) (median-based shock series), trimmed to end in 2015 Q4 for consistency with the baseline shock series.

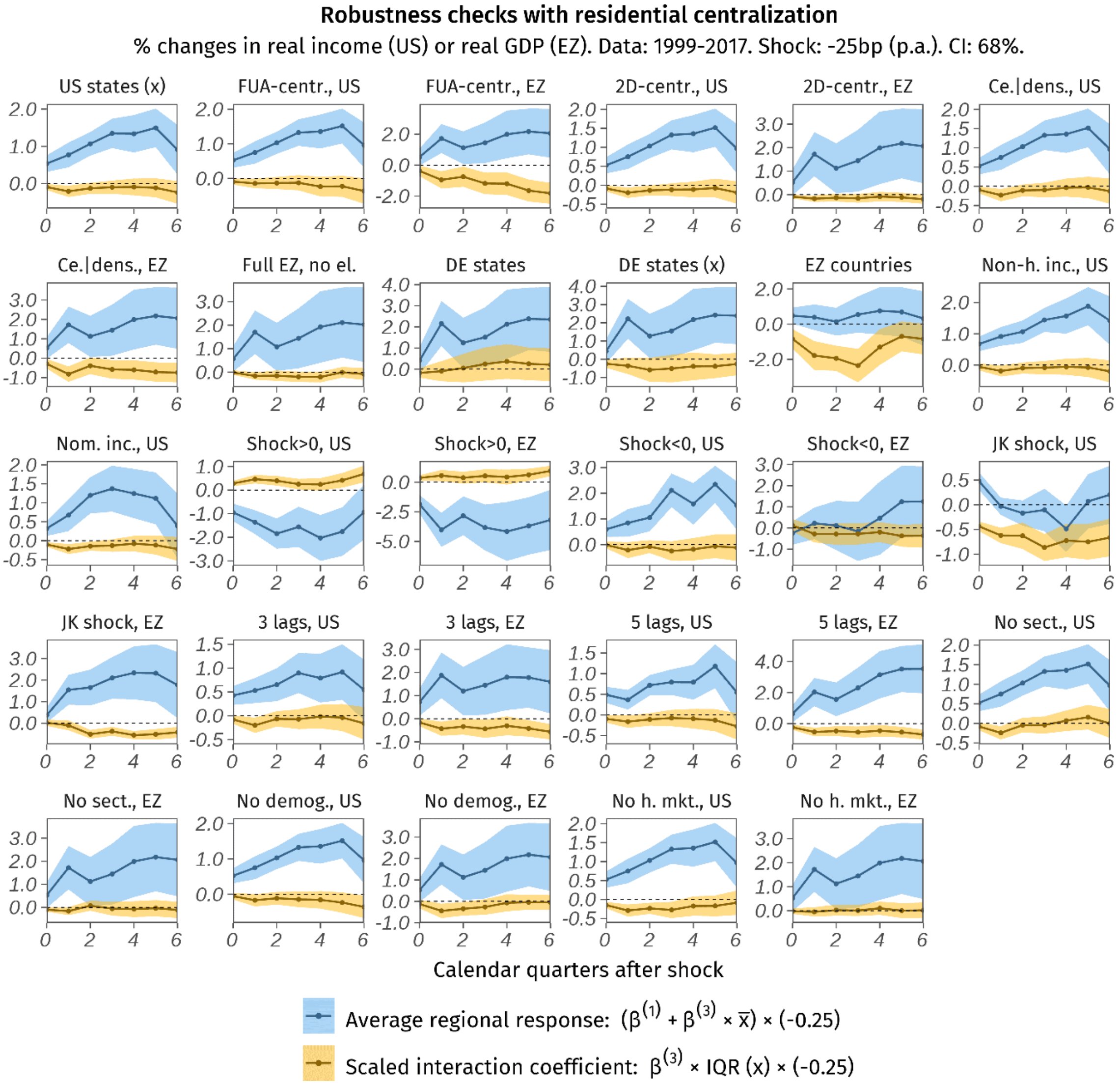
Table B.2: Summary statistics of data used in the empirical analysis, Eurozone

Variable	N	Avg	SD	Min	Mdn	Max
Region	25	–	–	–	–	–
Calendar quarter	73	–	–	1999 Q2	–	2017 Q2
Res. centralization (urban center) (in %)	1,575	32	24	7	26	96
Res. centralization (FUA) (in %)	1,575	54	23	11	52	100
Res. centr.: 2D (urban center) (in %)	1,575	21	24	3	13	93
Res. clustering (1×1) (in thsd m^3)	1,575	139	43	58	146	222
Res. clustering (3×3) (in thsd m^3)	1,575	993	347	387	975	1,768
Res. clustering (5×5) (in thsd m^3)	1,575	2,330	903	887	2,162	4,597
Res. clustering (7×7) (in thsd m^3)	1,575	4,006	1,701	1,509	3,548	8,607
Res. clustering: 2D (3×3) (in thsd m^2)	1,575	87	26	35	83	160
Res. density (in thsd m^3 / km^2)	1,575	191	278	3	82	1,145
Res. d.: only built-up area (in thsd m^3 / km^2)	1,575	325	297	32	209	1,340
Res. density: 2D (in thsd m^2 / km^2)	1,575	28	30	1	17	131
Monetary policy shock (baseline, in bp p.a.)	67	1	5	−21	1	13
Monetary policy shock (alternative, in bp p.a.)	67	1	6	−10	1	21
EONIA or shadow rate (in % p.a.)	63	1.9	1.8	−1.9	2.1	4.8
Eurozone HICP inflation (in %, quarterly)	63	0.5	0.3	−0.5	0.5	1.1
Construction sector GVA share (in %)	1,575	5.2	1.9	1.2	5.0	12.5
Manufacturing sector GVA share (in %)	1,575	19.7	5.5	8.9	19.6	39.1
Primary sector GVA share (in %)	1,575	1.5	1.0	0.0	1.6	4.9
Share of population aged > 64 (in %)	1,575	18.7	2.8	10.8	18.8	25.1
Share of population aged < 20 (in %)	1,575	20.0	3.1	14.0	19.8	30.7
Residential built-up volume share (in %)	1,575	75	5	59	76	85
Housing construction elasticity	25	0.70	0.20	0.40	0.67	1.30

Notes: The sample includes Austria, Belgium, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, and the 16 German states. This choice is based on the availability of regional GDP data and housing construction elasticity estimates. Real GDP is not included in the table due to a lack of straightforward interpretability. Spatial measurements, sectoral composition, and demographics are linearly interpolated at the quarterly level.
The beginning of the sample is 1999, with the introduction of the euro. Due to using lagged interaction variables and 4 lags of other variables, the (main) estimation starts in 2000 Q2. The end of the sample is synchronized to the end of the US sample. The table reports values that enter the regressions directly.
The baseline monetary policy shocks are from Gulyas et al. (2024). The alternative monetary policy shocks are from Jarociński and Karadi (2020) (median-based shock series), trimmed to end in 2015 Q4 for consistency with the baseline shock series.

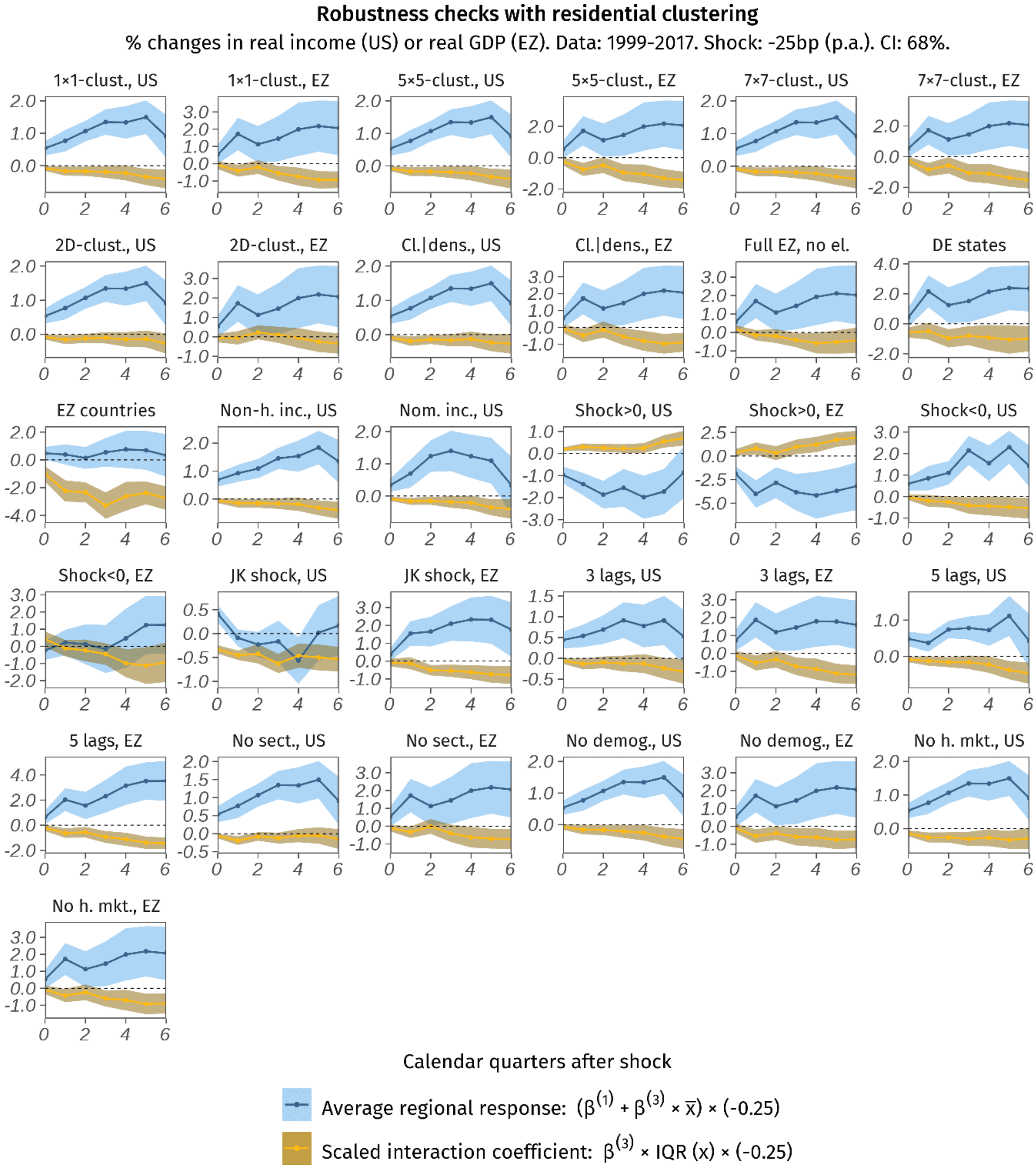
Appendix B4: Empirical robustness checks

Figure B.2: The empirical result with residential centralization is robust



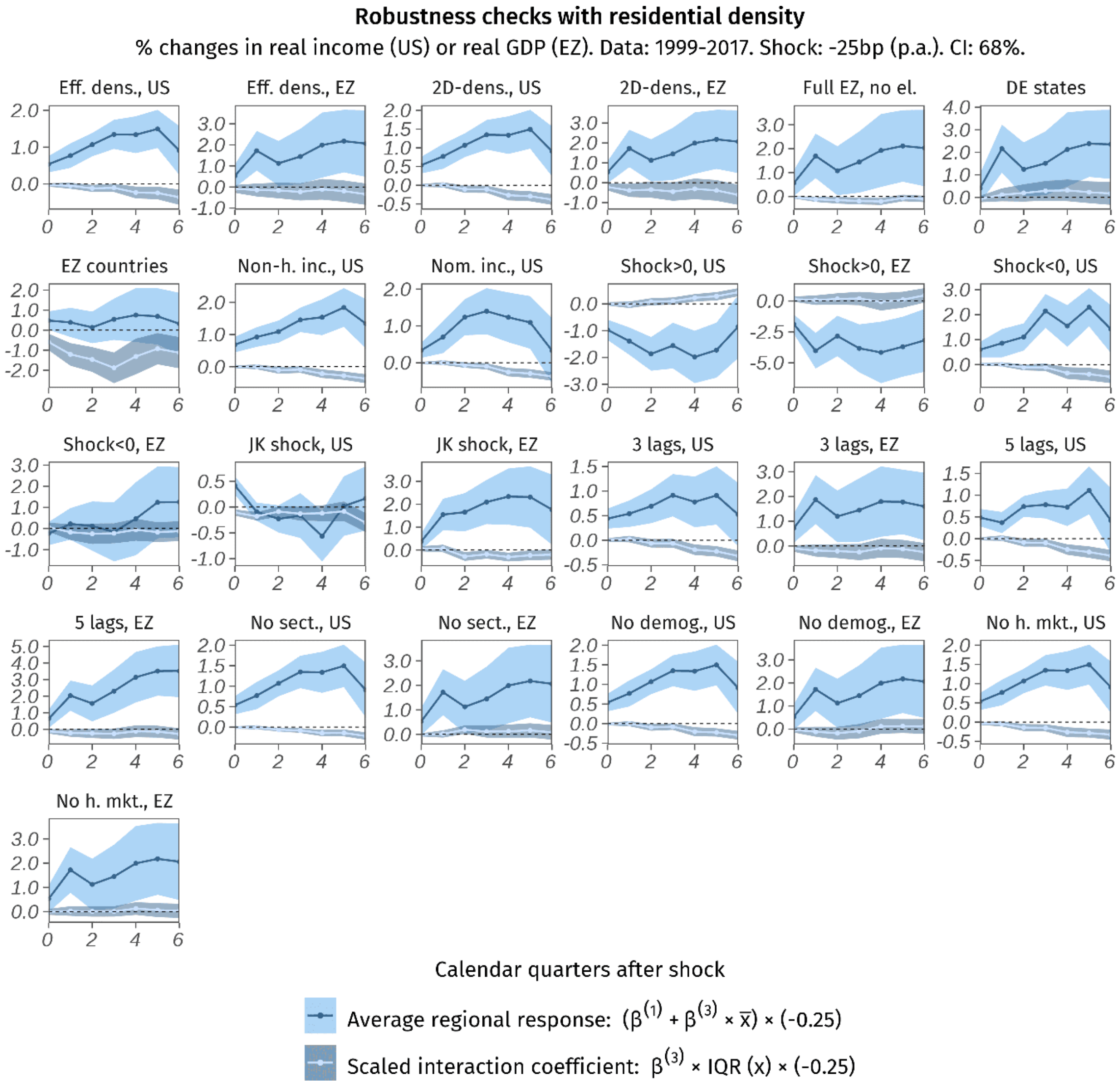
Notes: The blue lines show the average regional responses to a monetary policy shock. The brown lines show the interaction coefficients between the shocks and the spatial variable of interest, scaled by the interquartile range of that variable. The estimation for the US uses data from contiguous US states except for New Hampshire; the estimation for the Eurozone uses data from Austria, Belgium, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, and the 16 German states.
"US states (x)" refers to including states that are particularly prone to measurement error for urban center boundaries based on Figure B.1, that is, states for which residential centralization changed by more than 5.5 percentage points between 2000 and 2015 at 5-year intervals at least once. "FUA-centr." refers to using functional urban area boundaries instead of urban center boundaries. "2D-centr." refers to using data on residential built-up surface instead of residential built-up volume. "Ce.|dens." refers to including the naive measure of residential density as a control variable. "Full EZ, no el." refers to the specification with all Eurozone countries (a country is included in the sample when it enters the Eurozone), where I have to exclude the housing construction elasticity control due to data limitations. "DE states" and "EZ countries" refer to regressions with respective subsamples. "DE states (x)" excludes Berlin. "Non-h. inc." refers to using the CPI without shelter expenditures for deflation and excluding "real estate and rental and leasing" from total state-level income. "Nom. inc." refers to using nominal state-level income. "Shock>0" and "Shock<0" refer to only including contractionary or expansionary shocks in the estimation. "JK shock" refers to using the alternative shock series from Jarociński and Karadi (2020). "3 lags" and "5 lags" refer to changing the number of lags. "No sect.", "No demog.", and "No h. mkt." refer to excluding the control variable blocks for sectoral composition, demographics, and housing market characteristics.

Figure B.3: The empirical result with residential clustering is robust



Notes: The blue lines show the average regional responses to a monetary policy shock. The orange lines show the interaction coefficients between the shocks and the spatial variable of interest, scaled by the interquartile range of that variable. The estimation for the US uses data from contiguous US states except for New Hampshire; the estimation for the Eurozone uses data from Austria, Belgium, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, and the 16 German states.
"1×1-clust.", "5×5-clust.", and "7×7-clust." refer to changing the extent of the local exposure window for the measurement of residential clustering. "2D-clust." refers to using data on residential built-up surface instead of residential built-up volume. "Cl.|dens." refers to including the naive measure of residential density as a control variable. "Full EZ, no el." refers to the specification with all Eurozone countries (a country is included in the sample when it enters the Eurozone), where I have to exclude the housing construction elasticity control due to data limitations. "DE states" and "EZ countries" refer to regressions with respective subsamples. "Non-h. inc." refers to using the CPI without shelter expenditures for deflation and excluding "real estate and rental and leasing" from total state-level income. "Nom. inc." refers to using nominal state-level income. "Shock>0" and "Shock<0" refer to only including contractionary or expansionary shocks in the estimation. "JK shock" refers to using the alternative shock series from Jarociński and Karadi (2020). "3 lags" and "5 lags" refer to changing the number of lags. "No sect.", "No demog.", and "No h. mkt." refer to excluding the control variable blocks for sectoral composition, demographics, and housing market characteristics.

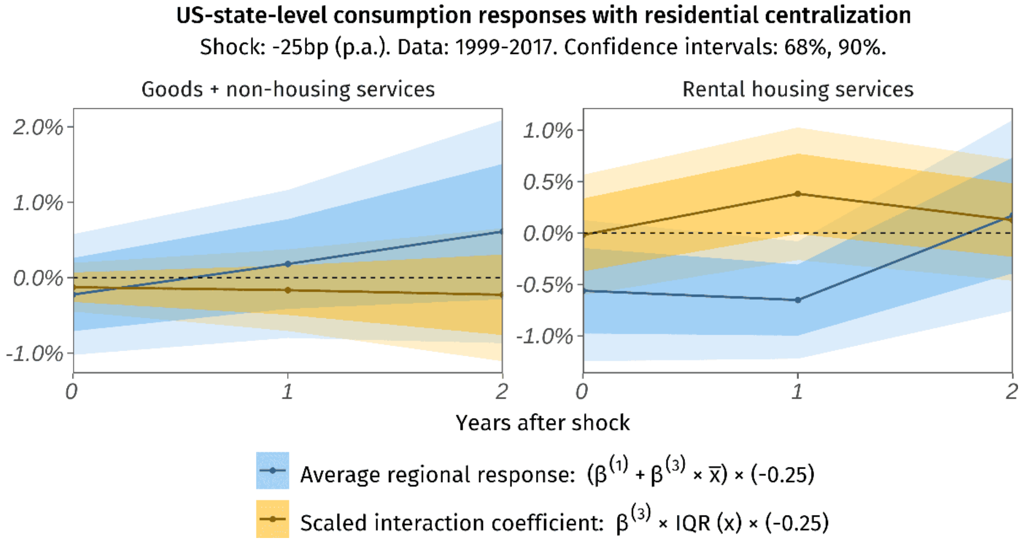
Figure B.4: The empirical null result with residential density is robust



Notes: The dark blue lines show the average regional responses to a monetary policy shock. The light blue lines show the interaction coefficients between the shocks and the spatial variable of interest, scaled by the interquartile range of that variable. The estimation for the US uses data from contiguous US states except for New Hampshire; the estimation for the Eurozone uses data from Austria, Belgium, Finland, France, Ireland, Italy, the Netherlands, Portugal, Spain, and the 16 German states.
"Eff. dens." refers to excluding empty 300 m × 300 m cells for the calculation of residential density. "2D-dens." refers to using data on residential built-up surface instead of residential built-up volume. "Full EZ, no el." refers to the specification with all Eurozone countries (a country is included in the sample when it enters the Eurozone), where I have to exclude the housing construction elasticity control due to data limitations. "DE states" and "EZ countries" refer to regressions with respective subsamples. "Non-h. inc." refers to using the CPI without shelter expenditures for deflation and excluding "real estate and rental and leasing" from total state-level income. "Nom. inc." refers to using nominal state-level income. "Shock>0" and "Shock<0" refer to only including contractionary or expansionary shocks in the estimation. "JK shock" refers to using the alternative shock series from Jarociński and Karadi (2020). "3 lags" and "5 lags" refer to changing the number of lags. "No sect.", "No demog.", and "No h. mkt." refer to excluding the control variable blocks for sectoral composition, demographics, and housing market characteristics.

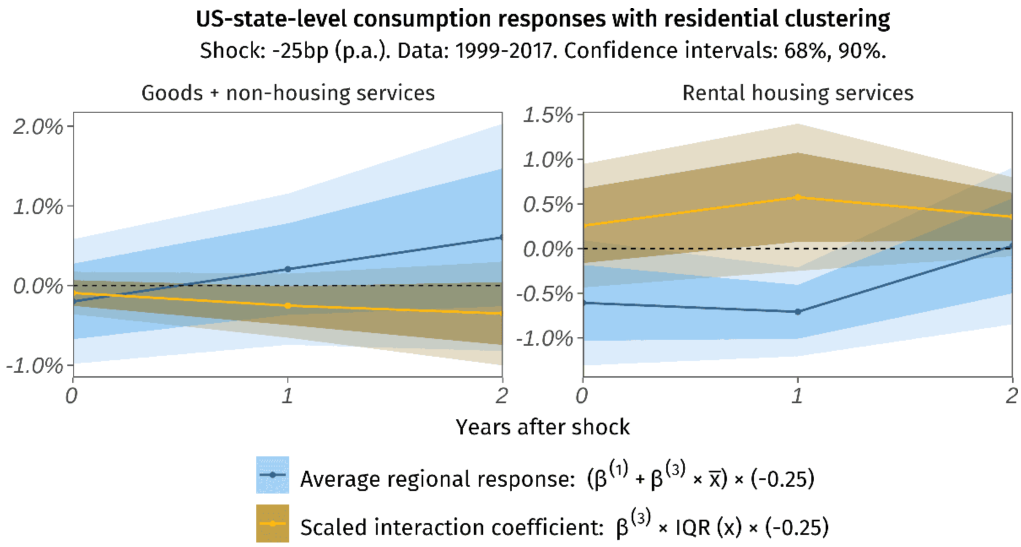
Appendix B5: Empirical results with annual US consumption data

Figure B.5: The centralization-based results hold with annual US consumption data



Notes: The blue lines show the average regional responses to a monetary policy shock. The brown lines show the interaction coefficients between the shocks and residential centralization, scaled by the interquartile range of the respective spatial measure. The consumption responses are estimated with an annual panel of contiguous US states except for New Hampshire, using the same data as in the main estimation. Annual values are obtained via sums or averages of quarterly values, depending on which is applicable. Monetary policy shocks are summed. The local projections use one annual lag. The consumption data are derived from the BEA Regional accounts: state personal consumption expenditures, current dollar prices (SAPCE3; 2: goods, 48: household consumption expenditures (for services), 50: housing, 52: imputed rental of owner-occupied nonfarm housing). The estimation uses all consumption categories except for imputed rentals and consumption expenditures of nonprofit institutions serving households.

Figure B.6: The clustering-based results hold with annual US consumption data



Notes: The blue lines show the average regional responses to a monetary policy shock. The orange lines show the interaction coefficients between the shocks and residential clustering, scaled by the interquartile range of the respective spatial measure. See Figure B.5 for details on the estimation. Consistent with the results using US-state-level income, the interaction effects are more pronounced in the specification with clustering (compared to centralization) when using consumption as the outcome variable.