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Essays on Home Renovation and Frictions in the Housing Market

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Economics

by

Yeonjoo Son

June 2026

Dissertation Committee:

Prof. Victor Ortego-Marti, Chairperson
Prof. Jang-Ting Guo
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Prof. Bree Lang
Prof. Miroslav Gabrovski

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2026

The Dissertation of Yeonjoo Son is approved:

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University of California, Riverside

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To my parents, with all my gratitude.

ABSTRACT OF THE DISSERTATION

Essays on Home Renovation and Frictions in the Housing Market

by

Yeonjoo Son

Doctor of Philosophy, Graduate Program in Economics
University of California, Riverside, June 2026
Prof. Victor Ortego-Marti, Chairperson

This dissertation studies home renovation in housing market dynamics, combining search-and-matching theory with new empirical evidence from the United States. The three chapters examine how renovation interacts with housing market frictions, credit market frictions, and household collateral constraints.

Chapter 1 develops a search-and-matching model with endogenous renovation. Using aggregate U.S. data, I document new stylized facts: renovation comoves positively with prices, vacancies, and sales, and negatively with time-on-market. The calibrated model replicates these elasticities and shows that endogenous renovation is an essential adjustment margin.

Chapter 2 adds a frictional credit market for renovation financing. Calibrated to the 2012–2019 U.S. housing recovery, the model implies that the credit channel barely affects average prices but accounts for about 64% and 71% of the declines in time-to-sell and the vacancy rate, through a novel compositional channel of liquidity.

Chapter 3 turns to the data. Using loan-level HMDA data for 2011–2024 and an instrumental variables design adapted from Chaney, Sraer, and Thesmar (2012), we identify a household collateral channel operating through renovation credit, concentrated where households hold more pledgeable collateral.

Collectively, the chapters establish renovation as an important channel linking housing markets, credit markets, and household collateral.

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General Introduction

Housing is the single largest asset on most household balance sheets and the primary source of pledgeable wealth in the economy. A defining feature of the housing market is that it is highly illiquid. Buyers and sellers must search for suitable matches, and transactions are subject to substantial and persistent frictions that generate fluctuations in prices, sales, vacancies, and especially time-on-market. Because housing is durable and spatially fixed, the existing stock is rarely replaced through new construction; instead, it is maintained, upgraded, and adapted through renovation. Renovation is therefore a central margin of adjustment in housing markets, yet it has received comparatively little attention relative to new construction and consumption.

Renovation is also large and growing. Private fixed investment in residential improvements amounts to hundreds of billions of dollars per year in the United States, has trended upward over time, and has become an increasing target of housing and energy policy. Renovation occupies a distinctive economic position. It generates immediate consumption value for the homeowner while simultaneously being embedded in the physical housing stock and capitalized into the future value of the property. In this sense renovation is at once consumption and investment, and it sits at the intersection of three frictions that organize this dissertation. These are search frictions in the housing market, credit market frictions in renovation financing, and household collateral constraints. Each of the three chapters studies renovation through the lens of one of these frictions.

This dissertation asks how renovation interacts with these frictions and what its aggregate consequences are. Three unifying questions connect the chapters. First, how does renovation interact with housing search frictions over the business cycle, and what role does it play in the cyclical co-movement of prices, sales, vacancies, and liquidity? Second, do credit market frictions in renovation financing transmit to housing-market liquidity, and through what channel? Third, do household collateral constraints shape renovation lending in the data, and how strong is the resulting household collateral channel? Across the three chapters, the analysis traces renovation from a theoretical adjustment margin in the housing market (Chapter 1), through the credit market that finances it (Chapter 2), to direct empirical evidence on the household collateral channel that drives it (Chapter 3).

Related Literature

This dissertation draws on and contributes to three strands of research. The first is the search-and-matching literature on housing markets, building on Wheaton (1990) and the Diamond–Mortensen–Pissarides tradition and developed in work such as Diaz and Jerez (2013), Genesove and Han (2012), Ngai and Tenreyro (2014), and Gabrovski and Ortego-Marti (2019). This literature studies the joint dynamics of prices, vacancies, sales, and time-on-market under frictions but has largely abstracted from renovation; Chapter 1 introduces renovation as an endogenous decision margin into this framework. The second strand concerns credit market frictions and their interaction with housing. Building on the frictional credit market of Wasmer and Weil (2004) and on housing models with financing constraints, Chapter 2 embeds a search-based renovation credit market into a housing model and studies how credit frictions transmit to housing-market liquidity. The third strand is the literature on the collateral channel, originating in the corporate-investment evidence of Chaney, Sraer, and Thesmar (2012) and the household housing-wealth literature (Mian & Sufi, 2011). Chapter 3 extends the collateral channel from the corporate to the household setting, using renovation lending as the closest household analog to collateral-financed corporate investment.

Outline of the Dissertation

Chapter 1 develops a search-and-matching model of the housing market with endogenous renovation decisions. Using aggregate U.S. data, it documents new stylized facts. Renovation activity comoves positively with prices, vacancies, and sales, and negatively with time-on-market. To account for these patterns, the chapter builds a model with a heterogeneous housing stock, free entry, and a renovation threshold that governs households' renovation choices. Once calibrated, the model replicates the observed elasticities both qualitatively and quantitatively, and counterfactual exercises show that the endogenous response of renovation is essential for housing-market variables to track the cyclical behavior observed in the data. Renovation thus operates as an additional adjustment margin, alongside buyer and seller entry, that shapes the cyclical co-movement of housing-market liquidity.

Chapter 2 extends the framework to a frictional credit market for renovation financing, in which homeowners obtain external financing to upgrade their homes from low- to high-quality, with free entry and Nash bargaining in both the housing and credit markets. Calibrating the model to the 2012–2019 U.S. housing recovery, the chapter finds that the renovation credit channel has a negligible effect on the average house price but contributes substantially to the recovery in housing-market liquidity, accounting for roughly 64% and 71% of the declines in time-to-sell and the vacancy rate, respectively. The channel operates through a novel composition effect, whereby changes in the renovation flow shift the composition of vacancies and homeowners between low- and high-quality units, reshaping aggregate liquidity.

Chapter 3 provides empirical evidence on the household collateral channel for renovation lending. Using loan-level data from the Home Mortgage Disclosure Act (HMDA) for 2011–2024 and an instrumental-variables design adapted from Chaney et al. (2012), it instruments MSA-level house prices with the interaction of national mortgage rates and local housing supply elasticity, scaled by predetermined baseline collateral capacity. For an MSA at the sample mean of collateral capacity, a one-percent increase in instrumented house prices raises originated renovation lending by approximately $6,141, with effects concentrated in markets where households hold more pledgeable collateral at baseline. The effect is consistently stronger for originated loans than for the broader pool of applications, indicating that house price appreciation operates primarily through the realized supply of credit.

Contributions

Collectively, these three chapters establish renovation as an important margin connecting housing markets, credit markets, and household collateral. Chapter 1 identifies renovation as an endogenous adjustment margin that shapes the cyclical dynamics of housing-market liquidity; Chapter 2 shows that credit frictions transmit to that liquidity through a compositional channel; and Chapter 3 provides direct empirical evidence that household collateral values causally drive renovation lending. The dissertation thereby links a theoretical mechanism, its credit-market extension, and its empirical counterpart, and points to renovation as a previously underexplored margin in housing-market dynamics, one that shapes the cyclical behavior of prices and liquidity and links housing markets to the credit that finances them, with implications for housing policy and for the quality and energy efficiency of the aging U.S. housing stock.

Chapter 1

Home Renovation and Search Frictions in the Housing Market

Abstract

This paper studies the role of home renovation in shaping housing market dynamics over the business cycle. Using aggregate U.S. data, I document new stylized facts. Renovation activity is positively related to house prices, vacancies, and sales, and negatively related to time-on-market. To account for these patterns, I develop a search and matching model with endogenous renovation decisions, a heterogeneous housing stock, and free entry. The model generates a renovation threshold that governs households' renovation choices and, once calibrated, replicates the observed elasticities both qualitatively and quantitatively. Counterfactual exercises further show that the endogenous response of renovation activity is essential for housing market variables to track the cyclical behavior observed in the data, highlighting renovation as an important channel of housing market dynamics.

1.1 Introduction

One of the defining features of the housing market is the presence of search frictions: buyers and sellers must spend time and effort to find suitable matches, leading to delays in transactions. These frictions generate substantial and persistent fluctuations in key indicators such as prices, sales, vacancies, and especially time-on-market (a measure of liquidity). The pronounced volatility of time-on-market underscores the importance of accounting for search frictions in any analysis of housing market dynamics.

Another distinctive feature of the housing market is that, because housing is a spatially constrained asset, renovation plays a particularly prominent role. Houses are durable and immobile, tied to specific locations. Once built, they are rarely replaced with entirely new structures, and supply adjustments through new construction are inherently slow and geographically limited—particularly in dense urban areas.[1] Renovation therefore naturally emerges as a central mechanism for maintaining the existing housing stock and facilitating adjustment. It allows households to derive greater utility from improved living conditions and to keep their homes competitive in the market. Moreover, renovation activity has trended upward over time, with a particularly sharp increase in recent years, and has attracted growing attention from

[1] Brueckner (1986) and Arnott (1989) provide early theoretical treatments of spatial constraints in housing supply. Glaeser and Gyourko (2005) emphasize how land-use regulation further restricts new construction, while Saiz (2010) quantifies the impact of geographic constraints across U.S. metropolitan areas. In addition, according to the American Housing Survey, the median age of the U.S. housing stock was 44 years in 2023. See Appendix Figure 1.6, Panel (a).

policymakers.[2] Incorporating renovation is therefore essential for a comprehensive understanding of housing market dynamics.

This paper examines the cyclical properties of the housing market with particular emphasis on the role of renovation. While prior research has studied the joint dynamics of prices, vacancies, sales, and time-on-market within search and matching frameworks (e.g., Diaz and Jerez (2013), Gabrovski and Ortego-Marti (2019)), renovation has received little attention in these models. To address this gap, I analyze how homeowners' renovation decisions shape housing market outcomes. Using aggregate U.S. data, I document new stylized facts: the elasticities of prices, vacancies, and sales with respect to renovation are positive, while the elasticity of time-on-market is negative. These elasticities govern the movements of prices, vacancies, and market tightness—defined as the ratio of buyers to vacancies—which are the key state variables in search and matching models of housing, analogous to vacancies, unemployment, tightness, and wages in labor market search models (see Pissarides (2000)). I document these elasticities in Section 1.4 and present the model's fit in Section 1.5.

To account for these patterns, I develop a search and matching model in which households can endogenously choose to renovate. Buyers and sellers do not meet instantly: buyers search for suitable homes, while sellers wait to find the right buyer. These frictions are captured through a standard matching function that determines the probability of a successful transaction given the number of searching buyers and vacant houses. Houses exist in two states—non-renovated and renovated—and the probability that a buyer matches with each type depends on their relative shares in

[2] The ratio of renovation expenditure to GDP has risen steadily in recent years. Renovation expenditure is measured using the category "Private Fixed Investment in Residential Improvements" from the U.S. Bureau of Economic Analysis. See Appendix Figure 1.6, Panel (b). In addition, renovation has increasingly become a policy target. For instance, energy-efficiency and green-retrofit programs such as the Inflation Reduction Act enacted in 2022—administered by the U.S. Department of Energy and the U.S. Department of the Treasury—have further stimulated renovation activity.

the housing market. One of the key features of the model is that households draw idiosyncratic utility realizations for each house, so the same house may be valued differently across households. More specifically, this heterogeneity takes the form of match-specific utility: upon occupying a non-renovated home, the household draws a value that reflects how well the home fits its preferences.[3] In the model, this match-specific utility is the fundamental driver of renovation. When the match-specific utility is sufficiently high, the household undertakes renovation; otherwise, the home remains non-renovated. In other words, renovation is primarily motivated by customization. Although resale considerations are indirectly reflected through expected house values, the core mechanism operates through the customization motive.[4]

In this way, the analysis highlights how heterogeneity in match quality shapes renovation decisions and their aggregate implications.

The model uncovers a novel channel linking households' renovation decisions to housing market outcomes. I derive conditions for the renovation threshold in equilibrium and study its co-movement with market tightness and prices under free entry of buyers and sellers. To see this, consider first the impact of the renovation channel itself on the housing market. A match between a buyer and a seller generates a positive surplus, which is shared between them via bargaining. The presence of

[3] This match-specific utility is akin to the notion of idiosyncratic match productivity in labor search models (Mortensen and Pissarides (1994)), where heterogeneity across matches drives job creation and destruction.

[4] Survey evidence suggests that resale considerations account for only a minority of renovation activity. For example, the National Association of Realtors' *2025 Remodeling Impact Report* documents that roughly 18% of homeowners report renovating primarily in preparation for resale, while the remaining majority undertake renovation for reasons such as customization, upgrading outdated features, or improving comfort and functionality. Consistent with this evidence, the model treats customization as the central driver of renovation. In the baseline calibration, separating homeowners renovate before listing as a corner-solution simplification (see Section 2.2); robustness exercises in Appendix 1.6 show that the main results are unchanged when separating homeowners list as-is, or when only a small fraction renovate before listing. Behaviors such as house flipping, in which renovation is undertaken primarily to resell at a higher price (see, for example, Bayer, Geissler, Mangum, and Roberts (2020); Li, Yavas, and Zhu (2023)), are left for future research.

renovation channel expands the total surplus, and this higher surplus translates into higher negotiated prices. Thus, the renovation channel raises total surplus and transaction prices, which in turn encourage entry on both sides of the market and enhance liquidity in steady state. In addition to its steady state role, renovation interacts with cyclical conditions through a composition effect on listings, which functions as a third adjustment margin alongside buyer entry and seller entry. Intuitively, in a boom, buyers are more willing to enter the market as the value of homeownership rises, and sellers also have incentives to enter since time-on-market is shorter and selling prices are higher. At the same time, homeowners find renovation more attractive: higher utility value from the renovated house and higher expected sale prices lower the renovation threshold, inducing more households to renovate.[5] As a result, the share of renovated houses among listings rises, shifting the composition of the market toward higher-value units. Taken together, these forces generate higher prices, more vacancies, more sales, and shorter time-on-market in booms, consistent with the data, and underlie the renovation channel's contribution to the cyclical co-movement of housing market liquidity with prices.

I calibrate the model to U.S. aggregate moments and target the elasticities that capture the new stylized facts. The calibrated economy successfully reproduces these elasticities both quantitatively and qualitatively, linking renovation activity to prices, time-on-market, vacancies, and sales in response to aggregate housing market shocks. Moreover, the model aligns well with other key moments emphasized in the literature, such as the elasticities of prices with respect to time-on-market, vacancies, and sales, providing confidence that it captures the underlying dynamics of the U.S. housing market.

[5] In addition, higher house prices strengthen homeowners' borrowing capacity, further easing financing constraints for renovation. Since the focus of this paper is on the renovation channel, I abstract from collateral considerations and leave them for future research.

Beyond replicating these empirical patterns, two counterfactual exercises further clarify the role of the renovation channel. The first shuts the channel down entirely, so that the model collapses to a standard housing search model. This specification recovers the qualitative pattern of an upward-sloping Beveridge curve, confirming that the model nests a well-behaved standard search environment as a special case. The second counterfactual holds renovation activity fixed at its steady-state level, preventing it from responding to the cycle. In this case, the remaining margins of adjustment must absorb the entire shock, and housing market variables overreact to aggregate shocks relative to the data. Together, these exercises show that the endogenous response of renovation activity is essential for housing market variables to track the cyclical behavior observed in the data, highlighting renovation as an important channel of housing market dynamics.

Related literature. This paper contributes to three strands of research. First, following the seminal work of Arnott (1989) and Wheaton (1990), many studies have applied Diamond–Mortensen–Pissarides style search and matching models to housing markets. One strand of the literature models the housing market with search and matching framework as in Pissarides (2000). Papers in this strand include Piazzesi and Schneider (2009), Novy-Marx (2009), Genesove and Han (2012), Anenberg (2016), Burnside, Eichenbaum, and Rebelo (2016), Diaz and Jerez (2013), Head, Lloyd-Ellis, and Sun (2014), Head, Sun, and Zhou (2016), Gabrovski and Ortego-Marti (2019, 2020, 2021a, 2021b, 2022) and Kotova and Zhang (2020). A related line of work emphasizes household cutoffs or reservation decisions as drivers of the housing market liquidity (see, e.g., Krainer (2001); Ngai and Tenreyro (2014); Ngai and Sheedy (2020, 2024)). I complement this literature by introducing the renovation channel as an endogenous decision margin into a housing search framework. This generates a renovation threshold that links match-specific quality to market tightness and prices, enabling the model to replicate the newly documented elasticities. Second, this paper relates to research on aggregate housing market volatility and cyclical dynamics. Prior studies emphasize the role of credit supply loosening (Justiniano, Primiceri, & Tambalotti, 2019), joint buyer–seller dynamics and internal mover behavior (Anenberg & Bayer, 2020), and borrowing constraints combined with search frictions (Eerola & Määttänen, 2018) as important sources of cyclical fluctuations. I contribute to this strand by showing how endogenous renovation decisions, when aggregated, constitute an additional and previously underexplored channel shaping housing market dynamics. In the baseline model, renovation operates as an additional adjustment margin alongside buyer and seller entry, shaping the cyclical co-movement of housing market variables. Third, outside the search and matching framework, a body of applied work studies renovation and housing quality investment using micro-level evidence. Gyourko and Saiz (2004) show that homeowners reduce reinvestment when market values fall below replacement costs, while Harding, Rosenthal, and Sirmans (2007) provide evidence that maintenance and renovation contribute to house price appreciation. Duca, Muellbauer, and Murphy (2021) survey housing and credit cycle dynamics and note that renovation is more common during booms, suggesting that the procyclicality of renovation warrants further investigation. However, the role of renovation in shaping housing market dynamics has not been incorporated into a formal equilibrium model of the housing market. I build on this literature by embedding these micro-level renovation behaviors into a structural search framework, thereby linking household renovation choices to aggregate fluctuations in liquidity, sales, and prices. In doing so, the paper provides a formal mechanism that rationalizes existing empirical findings on renovation and housing quality investment and clarifies their implications for housing market dynamics.

In sum, this paper documents new stylized facts linking renovation activity to key housing market variables, incorporates renovation as an endogenous margin into a housing search and matching framework, and shows that the calibrated model replicates these empirical patterns both quantitatively and qualitatively. More broadly, the analysis highlights renovation as an important channel of housing market dynamics.

The remainder of the paper is organized as follows. Section 2.2 describes the model environment and decision problems. Section 2.2.4 characterizes the equilibrium, including the renovation threshold and entry conditions. Section 1.4 documents new stylized facts on the cyclical co-movement between renovation activity and key housing market variables. Section 1.5 discusses calibration and quantitative results. Section 2.4 concludes.

1.2 The housing market

This section introduces the housing market environment and the renovation decision. There are three types of agents: buyers, sellers, and homeowners, and two types of houses in the market, renovated and non-renovated. Upon entering the market, a buyer may match with either a renovated or a non-renovated seller, depending on the composition of listings. Both buyers and sellers face search frictions, as they must spend time and resources to find a trading partner. When a match occurs, the price is determined through bargaining; the seller exits the market, and the buyer becomes a homeowner. Renovation in the model arises through two essential decisions. First, a homeowner who draws a sufficiently high match-specific utility chooses to renovate; this decision applies both to long-standing homeowners and to recent buyers, who enter the homeowner pool immediately upon purchase and face the same renovation problem. Second, when a homeowner receives a separation shock and becomes a seller, the seller chooses whether to list the house as-is or to renovate before listing. Together, these two decisions encompass the renovation behavior of homeowners, sellers, and recent buyers (the customize-after-purchase margin). Once renovation takes place, the homeowner enjoys higher utility and becomes a renovated homeowner. Further details of the environment and equilibrium conditions are provided below.

1.2.1 The Environment

Time is discrete. Agents are risk-neutral, infinitely lived, and discount the future at rate β. To capture housing depreciation, at the beginning of the period a fraction δ of all houses, including vacancies, are destroyed. Moreover, search frictions in the housing market imply that it takes time for buyers to find a suitable house and for sellers to find a buyer. Following Diaz and Jerez (2013), Genesove and Han (2012), Head et al. (2014), Head et al. (2016), Novy-Marx (2009), and Wheaton (1990), I model these search frictions with a matching function based on the framework in Pissarides (2000). The matching technology gives the total number of contacts between searching buyers and sellers.

$$M = M(b, v^R + v^N), \tag{1.1}$$

where b is the number of buyers, v^R is the number of renovated house vacancies, and v^N is the number of non-renovated house vacancies. The matching technology is homogeneous of degree one, and increasing and concave with respect to both arguments. Buyers do not sort across house types ex ante; instead, they meet renovated and non-renovated vacancies in proportion to their relative shares in the listing pool.

The number of matches between each type of house vacancy and buyers is therefore given by

$$M^R = \frac{v^R}{v} M(b, v^R + v^N), \tag{1.2}$$

$$M^N = \frac{v^N}{v} M(b, v^R + v^N). \tag{1.3}$$

The transition rates for vacancies and buyers are derived from equations (2) and (3) by normalizing each by the relevant stock of vacancies or buyers. The rate at which a buyer finds a renovated house vacancy is $\frac{M^R}{b}$. The rate at which a buyer finds a non-renovated house vacancy is $\frac{M^N}{b}$. The rate at which a renovated house vacancy finds a buyer is $\frac{M^R}{v^R}$. The rate at which a non-renovated house vacancy finds a buyer is $\frac{M^N}{v^N}$.

$$\frac{M^R}{b} = (1-\phi)M(1, \theta^{-1}) \equiv (1-\phi)m(\theta), \tag{1.4}$$

$$\frac{M^N}{b} = \phi M(1, \theta^{-1}) \equiv \phi m(\theta), \tag{1.5}$$

$$\frac{M^R}{v^R} = M(\theta, 1) \equiv \theta m(\theta), \tag{1.6}$$

$$\frac{M^N}{v^N} = M(\theta, 1) \equiv \theta m(\theta), \tag{1.7}$$

where ϕ denotes the ratio of non-renovated house vacancies, defined as $\frac{v^N}{v}$, and θ represents housing market tightness, defined as $\frac{b}{v}$.

Consistent with prior studies, I abstract from the rental market and treat it as separate from the owner-occupied housing market. Glaeser and Gyourko (2007) show that arbitrage between rental and owner-occupied homes is limited due to fundamental differences in their characteristics. Similarly, Bachmann and Cooper (2014) document that transitions between tenure categories are largely contained within each market, are acyclical, and unrelated to vacancy rates in the rental sector. Taken together, these findings suggest that treating the rental market as separate from the owner-occupied market is reasonable.[6]

1.2.2 Bellman equations

Let H_R and H_N denote the value functions of a homeowner for renovated and non-renovated houses. The Bellman equations for renovated and non-renovated house homeowners are given by

$$H_R(\epsilon) = x\mu^H\epsilon + (1-\delta)\Big((1-s)\Big((1-\sigma)\beta H_R(\epsilon) + \sigma\beta H_N\Big) + s\beta V_R\Big), \tag{1.8}$$

$$\begin{aligned} H_N = x\mu^N + (1-\delta)\Big[(1-s)\Big((1-\lambda)\beta H_N + \lambda \int max\{\beta H_N, \beta H_R(\tau) - k^R\} dG(\tau)\Big) \\ + s \cdot max\{\beta V_N, \beta V_R - k^R\}\Big]. \end{aligned} \tag{1.9}$$

where x, μ^H, and μ^N represent the utility associated with home ownership. Here x denotes the aggregate flow utility from housing services, while μ^H and μ^N capture the relative quality of renovated and non-renovated homes, respectively. I normalize $\mu^N = 1$ and denote $\mu^H = \mu > 1$. Match-specific utility ϵ is realized only after renovation, so renovated homeowners enjoy $x\mu\epsilon$ whereas non-renovated ones enjoy x. In summary, homeowners derive utility of $x\mu\epsilon$ and x, respectively. With probability $1-\delta$, the house is not depreciated. Moreover, with probability $1-s$, homeowners do not receive a separation shock. In equation (1.8), at the rate σ, a downgrade shock occurs, and the owners of renovated houses become non-renovated house owners in the next period, with value $\sigma\beta H_N$. If homeowners do not receive a downgrade shock

[6] Several studies model rental and owner-occupied housing markets jointly under search frictions, allowing for interactions across tenure choices and market tightness; see, for example, Han, Ngai, and Sheedy (2022), Kumar (2024), and Bø (2021). While these papers provide valuable insights into tenure dynamics, my analysis abstracts from the rental sector to isolate the role of renovation.

with probability $1-\sigma$, they remain as owners of renovated houses, which yields a present value of $\beta H_R(\epsilon)$. If separation occurs with probability s, homeowners become sellers in the next period, with value $s\beta V_R$.

In equation (1.9), non-renovated owners draw a new match value τ with probability λ from the distribution $G(\tau)$, where $\tau \in [0,\infty]$. If $\tau > \epsilon_R$, they renovate, paying renovation cost k^R and transitioning to $\beta H_R(\tau)$; otherwise they remain non-renovated with continuation value βH_N. The threshold ϵ_R is defined by the indifference condition $\beta H_R(\epsilon_R) - k^R = \beta H_N$, so renovation follows a threshold rule. Intuitively, if the benefits from renovation exceed the renovation cost, homeowners will renovate. With probability $1-\lambda$, non-renovated house homeowners remain as non-renovated house homeowners with present value βH_N. If a separation shock s arrives, non-renovated owners choose whether to sell as-is or renovate before listing. For tractability, the baseline calibration adopts the parameter restriction $\beta V_R - k^R > \beta V_N$, under which renovation at separation is strictly optimal for all separating homeowners and the separation payoff reduces to $s(\beta V_R - k^R)$. This restriction yields a corner-solution simplification: in the baseline, separating homeowners renovate before listing.[7]

$$H_N = x + (1-\delta)\Big[(1-s)\Big(\big(1-\lambda(1-G(\epsilon_R))\big)\beta H_N + \lambda\int_{\epsilon_R}(\beta H_R(\tau)-k^R)dG(\tau)\Big) + s(\beta V_R - k^R)\Big]. \quad (1.10)$$

[7] Appendix 1.6 studies alternative specifications including the case in which all separating homeowners list the house as-is, and a mixed case in which only a small fraction renovate before listing. The main results are robust across these specifications.

The Bellman equations for sellers listing a house are

$$V_R = -c^V + (1-\delta)\Big((1-\theta m(\theta))\beta V_R + \theta m(\theta)\int_{\epsilon_R} p^R(\epsilon)\frac{dG(\epsilon)}{1-G(\epsilon_R)}\Big), \tag{1.11}$$

$$V_N = -c^V + (1-\delta)\Big((1-\theta m(\theta))\beta V_N + \theta m(\theta) p^N\Big). \tag{1.12}$$

Both types of sellers incur a flow cost of c^V. Equation (1.11) captures the value for renovated house sellers. Matching occurs at rate $\theta m(\theta)$, and they match with a buyer drawn from the truncated distribution $dG(\epsilon)/1 - G(\epsilon_R)$. Through bargaining, the seller receives the price $p^R(\epsilon)$ and leaves the market. The idiosyncratic match-specific utility ϵ is realized upon matching and is common knowledge to both parties. Accordingly, the seller observes how much the buyer values the house. Therefore, a seller considers this factor during bargaining when negotiating the price. Intuitively, if a buyer has high ϵ for the certain house, seller is able to negotiate higher price during bargaining. Equation (1.12) captures the value for non-renovated house sellers. Once they are matched with buyers, they receive the price p^N and leave the market.

On the buyer side, buyers can be matched with both types of sellers, renovated and non-renovated. Recall that ϕ denotes the share of non-renovated houses among houses for sale, i.e., $\phi \equiv v^N/v$.

$$\begin{aligned} B = {} & -c^B(b) + (1-m(\theta))\beta B \\ & + m(\theta)\Big(\phi(\beta H_N - p^N) + (1-\phi)\int_{\epsilon_R}(\beta H_R(\tau) - p^R(\tau))dG(\tau)\Big). \end{aligned} \tag{1.13}$$

Buyers incur a flow cost of $c^B(b)$. As more buyers enter the housing market, the search cost of buyers will also increase. $c^B(b)$ captures the congestion effect. They are matched with a seller at rate $m(\theta)$. With probability ϕ, buyers have a chance to meet a non-renovated house seller, and the match carries a net gain $\beta H_N - p^N$, whereas with probability $1-\phi$, the seller shows a renovated house, and the match yields a net surplus $\beta H_R(\tau) - p^R(\tau)$. Buyers form expectations about τ upon matching, and depending on its value, they decide whether to proceed with the purchase or not.

1.2.3 Nash Bargaining

The surplus from matching is split according to Nash Bargaining (Nash et al. (1950); Rubinstein (1982)). In the housing market, let $S^{BR} = \beta H_R(\epsilon) - p^R(\epsilon) - \beta B$ and $S^{BN} = \beta H_N - p^N - \beta B$ denote the buyer's surplus from a renovated and a non-renovated house, respectively. The seller's surplus from selling a renovated and a non-renovated house is denoted $S^{VR} = p^R(\epsilon) - \beta V_R$ and $S^{VN} = p^N - \beta V_N$. Then, the total surplus from matching is $S^i = S^{Bi} + S^{Vi}$ for $i = R, N$.

$$S^i = S^{Bi} + S^{Vi} = \beta H_i - \beta B - \beta V_i, \quad \text{for } i = R, N. \tag{1.14}$$

The prices of renovated and new houses, $p^R(\epsilon)$ and p^N, are solutions to the Nash bargaining problem.

$$p^R(\epsilon) = \arg\max_{p^R(\epsilon)} \Big(S^{VR}\Big)^{\eta} \Big(S^{BR}\Big)^{1-\eta}, \tag{1.15}$$

$$p^N = \arg\max_{p^N} \Big(S^{VN}\Big)^{\eta} \Big(S^{BN}\Big)^{1-\eta}, \tag{1.16}$$

where η represents the seller's bargaining strength and $1-\eta$ represents the buyer's bargaining strength in the housing market. The first-order condition for the bargaining problem satisfies the following rule,

$$\eta S^{Bi} = (1-\eta) S^{Vi}, \quad \text{for } i = R, N. \tag{1.17}$$

The Nash Bargaining rules (17) imply the following conditions, $S^{Vi} = \eta S^i$ and $S^{Bi} = (1-\eta)S^i$ for $i = R, N$. Intuitively, with Nash Bargaining, both negotiating parties receive their outside option. In addition, the seller receives a share η of the total surplus, whereas the buyer receives a share $1-\eta$. By substituting the surplus terms, we can derive the price equations.

$$p^R(\epsilon) = \eta(\beta H_R(\epsilon) - \beta B) + (1-\eta)\beta V_R, \quad \forall \epsilon > \epsilon_R, \tag{1.18}$$

$$p^N = \eta(\beta H_N - \beta B) + (1-\eta)\beta V_N. \tag{1.19}$$

The price equations highlight how transaction prices depend on both the continuation values of buyers and sellers. To obtain closed-form expressions, these equations must be solved jointly with the Bellman equations in equilibrium.

1.3 Equilibrium

This section characterizes the equilibrium of the housing market. Equilibrium conditions link the behavior of buyers, sellers, and homeowners to market tightness, the renovation threshold, and prices. Formally, equilibrium is defined by four sets of conditions: (i) free entry of sellers ($V_N = k$)[8], (ii) free entry of buyers ($B = 0$), (iii) the renovation threshold condition, and (iv) Nash-bargained prices. Together, these conditions determine the endogenous objects of the model, including market tightness, the renovation threshold, and prices. Intuitively, free entry of sellers implies that they enter the market until the value of a vacancy covers the construction cost k. On the

[8]Free entry applies to non-renovated vacancies; renovated vacancies are supplied through separations in the model.

buyer side, households participate in the market if the value of being a buyer, B, is positive. A key feature of the model is the renovation threshold condition,

$$H_R(\epsilon_R) - k^R = H_N, \tag{1.20}$$

which states that a non-renovated homeowner who draws ϵ_R is indifferent between renovating and remaining with a non-renovated house.

By combining the Bellman equation (1.12) and the free entry condition $V_N = k$, I derive the Housing Entry condition (HE),

$$\text{(HE):} \quad \frac{(1-(1-\delta)\beta)k + c^V}{\theta m(\theta)(1-\delta)} = p^N - \beta k. \tag{1.21}$$

Sellers enter the housing market until the entry cost equals the expected net value of the house. Intuitively, the left-hand side captures the expected costs of finding a buyer, which includes the search cost c^V and the user cost $(1-(1-\delta)\beta)k$ over the expected duration of the vacancy, $1/\theta m(\theta)$. The right-hand side corresponds to the expected seller's surplus, $p^N - \beta k$. This entry condition leads to endogenous dynamics among sellers.

Next, I consider the entry condition for buyers. By applying the free entry condition $B = 0$ and combining the Bellman equation for buyers with the Nash bargaining rules, I derive the Buyer Entry (BE) condition,

$$\text{(BE):} \quad \frac{c^B(b)}{m(\theta)} = \frac{1-\eta}{\eta}\left\{\phi(p^N - \beta k) + (1-\phi)(1-G(\epsilon_R))(\bar{p}^R - \beta V_R)\right\}, \tag{1.22}$$

where $\bar{p}^R = \int_{\epsilon_R} p(\epsilon)\frac{dG(\epsilon)}{1-G(\epsilon_R)}$ represents the average price of a renovated house. The BE condition states that buyers enter until the expected search cost, $c^B(b)/m(\theta)$, equals their expected share of the surplus. Through Nash bargaining, buyers capture a fraction $(1-\eta)/\eta$ of the total surplus, which includes outcomes from meeting non-renovated sellers and renovated sellers.

To solve the V_R, from the Bellman equation (1.11), we can rewrite the equation as follows,

$$V_R = \frac{(1-\delta)\theta m(\theta)\bar{p}^R - c^V}{1-\beta(1-\delta)(1-\theta m(\theta))}. \tag{1.23}$$

By combining V_R with the Nash bargaining condition,

$$V_R = \frac{(1-\delta)\theta m(\theta)\eta\beta\bar{H}_R - c^V}{1-\beta(1-\delta)(1-\theta m(\theta)\eta)}. \tag{1.24}$$

Next, I rewrite the Bellman equations (1.8) and (1.10),

$$\bar{H}_R = \frac{x\mu\bar{\epsilon} + (1-\delta)(1-s)\sigma\beta H_N + (1-\delta)s\beta V_R}{1-\beta(1-\delta)(1-s)(1-\sigma)}, \tag{1.25}$$

$$H_N = \frac{x + (1-\delta)(1-s)\lambda(1-G(\epsilon_R))(\beta\bar{H}_R - k^R) + (1-\delta)s(\beta V_R - k^R)}{1-\beta(1-\delta)(1-s)\Big(1-\lambda(1-G(\epsilon_R))\Big)}. \tag{1.26}$$

where $\bar{\epsilon} \equiv E(\epsilon|\epsilon \geq \epsilon_R) = \int_{\epsilon_R} \epsilon \frac{dG(\epsilon)}{1-G(\epsilon_R)}$ represents the expected value of ϵ conditional on $\epsilon \geq \epsilon_R$, and $\bar{H_R} = \int_{\epsilon_R} H_R(\epsilon) \frac{dG(\epsilon)}{1-G(\epsilon_R)}$. The three equations above are interdependent, so we can solve for V_R, H_N, and $\bar{H_R}$ in closed form.

$$V_R = \frac{\tilde{\delta}\tilde{\eta}\,\bar{H}_R - c^V}{1-\tilde{\delta}(1-\tilde{\eta})}, \tag{1.27}$$

$$\bar{H}_R = \frac{x\mu\bar{\epsilon} - \dfrac{\tilde{\delta}(1-\tilde{s})c^V}{1-\tilde{\delta}(1-\tilde{\eta})} + \dfrac{\tilde{\delta}\tilde{s}\sigma}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}\Pi_x}{1-\tilde{\delta}\tilde{s}(1-\sigma) - \dfrac{\tilde{\delta}^2(1-\tilde{s})\tilde{\eta}}{1-\tilde{\delta}(1-\tilde{\eta})} - \dfrac{\tilde{\delta}\tilde{s}\sigma}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}\Pi_\eta}, \tag{1.28}$$

$$H_N = \frac{\Pi_x + \Pi_\eta \bar{H}_R}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}, \tag{1.29}$$

where $\tilde{\delta} \equiv \beta(1-\delta)$, $\tilde{s} \equiv 1-s$, $\tilde{\eta} \equiv \theta m(\theta)\eta$, $\tilde{\lambda} \equiv \lambda(1-G(\epsilon_R))$, $\Pi_x \equiv x - \tilde{\delta}\left(\frac{\tilde{s}\tilde{\lambda}+(1-\tilde{s})}{\beta}\right)k^R - \frac{\tilde{\delta}(1-\tilde{s})c^V}{1-\tilde{\delta}(1-\tilde{\eta})}$, and $\Pi_\eta \equiv \tilde{\delta}\tilde{s}\tilde{\lambda} + \frac{\tilde{\delta}^2(1-\tilde{s})\tilde{\eta}}{1-\tilde{\delta}(1-\tilde{\eta})}$.

Next, I derive the price equations. By combining the Nash bargaining conditions with the free entry conditions,

$$p^R(\epsilon) = \eta\beta H_R(\epsilon) + (1-\eta)\beta V_R, \tag{1.30}$$

$$p^N = \eta\beta H_N + (1-\eta)\beta k. \tag{1.31}$$

Substituting $H_R(\epsilon)$, V_R, and H_N from equations (1.28), (1.27), and (1.29) gives the price equations,

$$\text{(PPR):}\quad p^R(\epsilon) = \beta\left[\left(\eta + \frac{(1-\eta)\tilde{\delta}\tilde{\eta}}{1-\tilde{\delta}(1-\tilde{\eta})}\right)\bar{H}_R - \frac{(1-\eta)c^V}{1-\tilde{\delta}(1-\tilde{\eta})}\right], \tag{1.32}$$

$$\text{(PPN):}\quad p^N = \beta\left[\left(\frac{\eta\Pi_\eta}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}\right)\bar{H}_R + \frac{\eta\Pi_x}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})} + (1-\eta)k\right]. \tag{1.33}$$

By substituting equation (1.28) into $\bar{H}_R$, the full price equations are obtained. Intuitively, these price equations reflect the Nash bargaining outcome: sellers are compensated for their outside option (k or V_R) and receive a share η of the surplus, while buyers capture the remainder. Note that η represents the bargaining power of the sellers.

To ensure that non-renovated house homeowners prefer renovation before the house for sales, we require the following inequality $k^R < \beta(V_R - V_N)$. Substituting the explicit forms of V_R and V_N, we obtain,

$$k^R < \beta \left(\frac{\tilde{\delta}\tilde{\eta}\bar{H}_R - c^V}{1 - \tilde{\delta}(1 - \tilde{\eta})} - \frac{-c^V + (1 - \delta)\theta m(\theta) p^N}{1 - (1 - \delta)(1 - \theta m(\theta))\beta} \right) \tag{1.34}$$

This inequality implies that non-renovated homeowners optimally renovate before selling. If k^R exceeds the value difference between renovated and non-renovated states, renovation at separation would no longer occur. I assume equation (1.34) holds throughout the analysis.

1.3.1 Renovation threshold

We now turn to the characterization of the renovation threshold ϵ_R. From the homeowner Bellman equations and the renovation threshold condition, we obtain the Renovation Condition (RC):

$$\begin{aligned} \epsilon_R = & \frac{1}{x\mu} \Bigg\{ x + \Big(1 - (1 - \delta)\big[s + \lambda(1 - s)(1 - G(\epsilon_R))\big]\Big) k^R \\ & - \beta(1 - \delta)(1 - s)\Big[(\sigma - 1 + \lambda)H_N + (1 - \sigma)H_R(\epsilon_R) - \lambda(1 - G(\epsilon_R))\bar{H}_R\Big] \Bigg\}. \end{aligned} \tag{1.35}$$

Intuitively, the RC implies that a higher aggregate utility x lowers the threshold ϵ_R, so more homeowners choose to renovate. Conversely, a higher renovation cost k^R

raises the threshold, making renovation less attractive. An increase in the value of the homeowner, H_N or $H_R(\epsilon_R)$, also lowers ϵ_R and stimulates renovation. By contrast, the expected value of renovated homes, $\bar{H}_R$, moves in the same direction as the threshold: when many homeowners renovate, the marginal entrants have lower ϵ, which reduces the average utility of renovated houses and thus lowers $\bar{H}_R$.

To make further progress, I assume that the distribution of match-specific utility follows a Pareto distribution, as in Han et al. (2022) and Gabrovski and Ortego-Marti (2022):

$$G(\epsilon) = 1 - \left(\frac{\epsilon_m}{\epsilon}\right)^{\alpha}, \qquad \alpha > 1, \tag{1.36}$$

where ϵ_m is the minimum possible draw and α is the shape parameter. Under this distribution, the conditional expectation is

$$\bar{\epsilon} \equiv E[\epsilon \mid \epsilon \geq \epsilon_R] = \frac{\alpha}{\alpha - 1}\, \epsilon_R.$$

Substituting the Pareto distribution along with H_N, $H_R(\epsilon_R)$, and $\bar{H}_R$ yields the explicit RC condition:

$$\begin{aligned} \text{(RC):} \quad \epsilon_R = \frac{1}{x\mu} \Bigg\{ & (1 - \tilde{\delta}\tilde{s}) \frac{\Pi_x}{1 - \tilde{\delta}\tilde{s}(1 - \tilde{\lambda})} + \frac{1 - \tilde{\delta}\tilde{s}(1 - \sigma)}{\beta}\, k^R + \tilde{\delta}(1 - \tilde{s})\, \frac{c^V}{1 - \tilde{\delta}(1 - \tilde{\eta})} \\ & + \left[(1 - \tilde{\delta}\tilde{s})\, \frac{\Pi_\eta}{1 - \tilde{\delta}\tilde{s}(1 - \tilde{\lambda})} - \tilde{\delta}(1 - \tilde{s})\, \frac{\tilde{\delta}\tilde{\eta}}{1 - \tilde{\delta}(1 - \tilde{\eta})} \right] \bar{H}_R \Bigg\}. \end{aligned} \tag{1.37}$$

Because the RC is nonlinear, the comparative statics cannot be signed analytically in closed form. Numerical exercises verify that the predicted signs hold across the relevant parameter space, providing a consistent foundation for the equilibrium analysis that follows. Totally differentiating the RC yields the comparative statics

$$\frac{d\epsilon_R}{dx} < 0, \qquad \frac{d\epsilon_R}{dk^R} > 0.$$

Thus, higher utility from homeownership encourages renovation, while higher renovation costs make it less attractive.

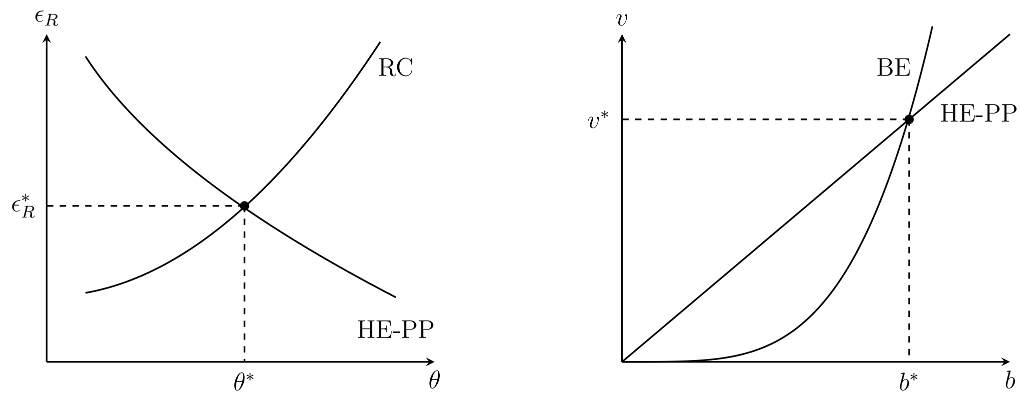
The comparative statics above illustrate how ϵ_R responds to fundamentals such as utility x and renovation cost k^R. To close the model, it is necessary to jointly determine market tightness θ and the renovation threshold ϵ_R. This is done by combining the housing entry condition (HE) with the price condition for non-renovated houses (PPN). Combine the HE and PPN conditions yields the following condition,

$$\frac{(1-(1-\delta)\beta)k + c^V}{\theta m(\theta)(1-\delta)} = \beta \left[\left(\frac{\eta \Pi_\eta}{1-\tilde{\delta}\tilde{s}(1-\lambda)} \right) \bar{H}_R + \frac{\eta \Pi_x}{1-\tilde{\delta}\tilde{s}(1-\lambda)} - \eta k \right]. \tag{1.38}$$

Intuitively, the left-hand side depends only on market tightness θ. When θ increases, the larger denominator reduces the left-hand side, capturing the lower effective cost of maintaining a vacancy in a hot market with abundant buyers. The right-hand side represents the seller's surplus. Although higher θ would mechanically raise surplus through faster matching, equilibrium requires the right-hand side to decline to offset the lower vacancy cost on the left-hand side. This adjustment occurs through the renovation threshold: in a hot market, ϵ_R decreases, more households choose to renovate, and lower-ϵ homes enter the renovated pool. As a result, the average match utility $\bar{\epsilon}$ falls, which reduces the expected value of renovated houses $\bar{H}_R$. This decline in $\bar{H}_R$ lowers the seller's surplus and ensures that the condition remains satisfied. This logic establishes a negative relationship between market tightness and the renovation threshold in equilibrium, as illustrated in Figure 1.1.

The RC condition implies a positive relationship between the renovation threshold ϵ_R and market tightness θ, i.e., $d\epsilon_R/d\theta > 0$. As more buyers enter the market, higher market tightness θ improves matching efficiency and increases market liquidity. In the model, renovation is a one time investment that raises match-specific utility and yields flow benefits over the duration of a household's stay in the house. An increase in market tightness θ raises households' outside options upon separation, reducing the incentive to invest in enhancing match-specific utility in the current match. As a result, the marginal value of renovation declines, and only households with sufficiently high match-specific utility optimally choose to renovate for their own enjoyment. Consequently, the renovation threshold ϵ_R increases with θ, and the RC curve slopes upward in the (θ, ϵ_R) space in Figure 1.1. Intuitively, stronger market liquidity weakens the incentive to undertake renovation aimed at enhancing match-specific utility, thereby raising the threshold required for renovation to occur.

Combining the RC curve with the housing entry condition (HE–PPN) determines a unique equilibrium pair (θ^*, ϵ_R^*), as illustrated in Figure 1.1. In equilibrium, market tightness and the renovation threshold adjust jointly to balance buyer and seller entry with household renovation incentives. Having determined the joint equilibrium in (θ, ϵ_R) space, I now turn to the (b, v) space. The right-hand panel of Figure 1.1 illustrates the Beveridge curve representation. The upward-sloping BE curve captures the positive relationship between buyers and vacancies. As the number of vacancies v increases, the expected search cost for buyers falls and the probability of finding a suitable match rises. This makes market participation more attractive, supporting a larger mass of buyers b. As noted by Gabrovski and Ortego-Marti (2019), this mechanism underlies the upward-sloping Beveridge curve in housing markets. The intersection of these two curves determines the equilibrium pair (b^*, v^*).



(a) Unique equilibrium

(b) Beveridge Curve

Figure 1.1: Equilibrium determination: Renovation threshold and Beveridge curve

Taken together, the two panels show that equilibrium requires consistency across both margins: on the one hand, (θ^*, ϵ_R^*) is jointly pinned down by the RC and HE–PPN conditions; on the other hand, (b^*, v^*) is jointly determined by the BE and HE–PP conditions. The unique equilibrium of the model is therefore given by the tuple $(\theta^*, \epsilon_R^*, b^*, v^*)$, jointly determined by buyer entry, seller entry, and the renovation threshold.

1.3.2 The laws of motion

The share of non-renovated vacancies, ϕ, follows from the laws of motion for homeowners and vacancies. Let h^R and h^N denote the measures of renovated and non-renovated homeowners, respectively, with $h = h^R + h^N$ the total. Similarly, let v^R and

v^N denote renovated and non-renovated vacancies, with $v = v^R + v^N$. The following laws of motion describe the dynamics of the homeowner measure.

$$h_{t+1}^R = h_t^R + b_t m(\theta_t)(1-\phi_t)\Big(1-G(\epsilon_{R,t})\Big) + \lambda\Big(1-G(\epsilon_{R,t})\Big)h_t^N - (\delta+s+\sigma)h_t^R, \tag{1.39}$$

$$h_{t+1}^N = h_t^N + b_t m(\theta_t)\phi_t - \Big(\delta+s+\lambda(1-G(\epsilon_{R,t}))\Big)h_t^N + \sigma h_t^R. \tag{1.40}$$

The evolution of homeowner stocks balances inflows and outflows. Equation (1.39) shows that h_{t+1}^R increases when buyers match with renovated vacancies, $b_t m(\theta_t)(1-\phi_t)(1-G(\epsilon_{R,t}))$, or when non-renovated owners choose to renovate, $\lambda(1-G(\epsilon_{R,t}))h_t^N$. Outflows occur through depreciation, separation, and downgrade shocks, $(\delta+s+\sigma)h_t^R$. Equation (1.40) shows that h_{t+1}^N rises when buyers match with non-renovated vacancies, $b_t m(\theta_t)\phi_t$, or when renovated homes downgrade, σh_t^R. It falls due to depreciation, separation, or renovation, $(\delta+s+\lambda(1-G(\epsilon_{R,t})))h_t^N$. Next, consider the dynamics of vacancies:

$$v_{t+1}^R = v_t^R + s\Big(h_t^N + h_t^R\Big) - \Big(\theta_t m(\theta_t)\Big(1-G(\epsilon_{R,t})\Big)+\delta\Big)v_t^R, \tag{1.41}$$

$$v_{t+1}^N = v_t^N + n_t - \Big(\theta_t m(\theta_t)+\delta\Big)v_t^N, \tag{1.42}$$

Equation (1.41) shows that renovated vacancies increase when separations occur, $s\Big(h_t^N + h_t^R\Big)$, and decrease when they are matched with buyers or destroyed, $\Big(\theta_t m(\theta_t)\Big(1-G(\epsilon_{R,t})\Big)+\delta\Big)v_t^R$. Equation (1.42) shows that non-renovated vacancies are supplied by new sellers, n_t, while outflows occur due to matching and destruction, $\Big(\theta_t m(\theta_t)+\delta\Big)v_t^N$. In steady state, all stocks are time-invariant. Setting

$h_{t+1}^R = h_t^R = h^R$, $h_{t+1}^N = h_t^N = h^N$, $v_{t+1}^R = v_t^R = v^R$, and $v_{t+1}^N = v_t^N = v^N$, the law of motion yields to the following steady state distributions:

$$h^R = \frac{bm(\theta)(1-\phi)(1-G(\epsilon_R)) + \lambda(1-G(\epsilon_R))h^N}{\delta+\sigma+s}, \tag{1.43}$$

$$h^N = \frac{bm(\theta)\phi + \sigma h^R}{\delta+s+\lambda(1-G(\epsilon_R))}, \tag{1.44}$$

$$v^R = \frac{s(h^N+h^R)}{\theta m(\theta)(1-G(\epsilon_R))+\delta}, \tag{1.45}$$

$$v^N = \frac{n}{\theta m(\theta)+\delta}. \tag{1.46}$$

Solving (43)–(44) jointly gives closed-form expressions for h^R and h^N:

$$h^R = \frac{bm(\theta)\Big(\phi\lambda(1-G(\epsilon_R)) + (1-\phi)(1-G(\epsilon_R))(\delta+s+\lambda(1-G(\epsilon_R)))\Big)}{(\delta+s)(\delta+s+\lambda(1-G(\epsilon_R))+\sigma)}, \tag{1.47}$$

$$h^N = \frac{bm(\theta)\Big(\phi(\delta+s+\sigma) + \sigma(1-\phi)(1-G(\epsilon_R))\Big)}{(\delta+s)(\delta+s+\lambda(1-G(\epsilon_R))+\sigma)}. \tag{1.48}$$

Adding these yields the total homeowner measure:

$$h = h^N + h^R = \frac{bm(\theta)}{\delta+s}\Big(\phi + (1-\phi)(1-G(\epsilon_R))\Big), \tag{1.49}$$

which is consistent with the housing search literature. Substituting into (45) provides the steady state distribution of renovated vacancies:

$$v^R = \frac{sbm(\theta)}{\Big(\theta m(\theta)(1-G(\epsilon_R))+\delta\Big)(\delta+s)}\Big\{1-(1-\phi)G(\epsilon_R)\Big\}. \tag{1.50}$$

Finally, ϕ is determined using $\phi = v^N/v$ and $v = b/\theta$:

$$\phi = \frac{v\,(\theta m(\theta)[1 - G(\epsilon_R)] + \delta)(\delta + s) - s\,b\,m(\theta)\,[1 - G(\epsilon_R)]}{v\,(\theta m(\theta)[1 - G(\epsilon_R)] + \delta)(\delta + s) + s\,b\,m(\theta)\,G(\epsilon_R)} \tag{1.51}$$

Definition 1. The *equilibrium* consists of a tuple $\{\theta, b, p^N, p^R, \epsilon_R, h^N, h^R, v^N, v^R, \phi, n\}$ that satisfies: (1) the (RC) condition; (2) the (PPN) condition; (3) the (PPR) condition; (4) the (HE) condition; (5) the (BE) condition; (6) the steady state distributions; (7) $\theta = b/v$.

This system consists of eleven equations in eleven unknowns, which jointly characterize the equilibrium of the model.

1.3.3 Business cycle

The steady state analysis above characterizes the static equilibrium of the housing market. To understand how the model behaves over the business cycle, I now extend the framework to a dynamic setting with stochastic shocks. The logic of the equilibrium remains the same: households choose whether to renovate, buyers and sellers enter subject to free-entry conditions, and prices are determined through Nash bargaining. However, in the dynamic environment, these choices and outcomes evolve over time in response to shocks that affect aggregate housing demand, separation, and renovation costs. This extension makes it possible to analyze the interaction between renovation and housing market frictions over cyclical fluctuations.

Let i denote the current state of the economy and i' the state next period. For any value function X, write X_i as its value in state i and $\mathbb{E}_i X_{i'}$ as the expectation of next period's value conditional on state i. The state i is defined by the pair (x_i, k_i), where x_i denotes aggregate housing utility and k_i the construction cost. I assume these shocks are perfectly correlated, so that the state can be represented by a single index

i. This structure parallels Shimer (2005), where a common state variable governs both labor productivity and separation rates. As in his framework, the calibration of the processes for x_i and k_i determines the implied correlation between the two shocks in the housing market.

Under this notation, the Bellman equations for homeowners, vacancies, and buyers take the same form as in the static model, except that they are indexed by state i and incorporate expectations over i'.

$$H_{R,i}(\epsilon_i) = x_i\mu\epsilon_i + (1-\delta)\Big((1-s)\Big((1-\sigma)\beta\,\mathbb{E}_i\,H_{R,i'}(\epsilon_{i'}) + \sigma\beta\,\mathbb{E}_i\,H_{N,i'}\Big) + s\beta\,\mathbb{E}_i\,V_{R,i'}\Big), \tag{1.52}$$

$$\begin{aligned} H_{N,i} = x_i + (1-\delta)\Bigg(&(1-s)\Big((1-\lambda(1-G(\epsilon_{R,i})))\beta\,\mathbb{E}_i\,H_{N,i'} \\ &+ \lambda\int_{\epsilon_{R,i}}(\beta\,\mathbb{E}_i\,H_{R,i'}(\tau_{i'}) - k_i^R)dG(\tau_i)\Big) + s(\beta\,\mathbb{E}_i\,V_{R,i'} - k_i^R)\Bigg), \end{aligned} \tag{1.53}$$

$$V_{R,i} = -c^V + (1-\delta)\Big((1-\theta_i m(\theta_i))\beta\,\mathbb{E}_i\,V_{R,i'} + \theta_i m(\theta_i)\int_{\epsilon_{R,i}} p^R(\epsilon_i)\frac{dG(\epsilon_i)}{1-G(\epsilon_{R,i})}\Big), \tag{1.54}$$

$$V_{N,i} = -c^V + (1-\delta)\Big((1-\theta_i m(\theta_i))\beta\,\mathbb{E}_i\,V_{N,i'} + \theta_i m(\theta_i)p_i^N\Big), \tag{1.55}$$

$$\begin{aligned} B_i = -c^B(b_i) + (1-m_i(\theta_i))\beta\,\mathbb{E}_i\,B_{i'} + m(\theta_i)\Big(&\phi_i(\beta\,\mathbb{E}_i\,H_{N,i'} - p_i^N) \\ &+ (1-\phi_i)\int_{\epsilon_{R,i}}(\beta\,\mathbb{E}_i\,H_{R,i'}(\tau_{i'}) - p^R(\tau_i))dG(\tau_i)\Big). \end{aligned} \tag{1.56}$$

Prices are thus determined through Nash bargaining: sellers receive their outside option and a share η of the match surplus, while buyers capture the remainder.

$$p^R(\epsilon_i) = \arg\max_{p^R(\epsilon_i)} \Big(p^R(\epsilon_i) - \beta\,\mathbb{E}_i\,V_{R,i'}\Big)^{\eta}\Big(\beta\,\mathbb{E}_i\,H_{R,i'}(\epsilon_{i'}) - p^R(\epsilon_i) - \beta\,\mathbb{E}_i\,B_{i'}\Big)^{1-\eta} \tag{1.57}$$

$$p_i^N = \arg\max_{p^N} \Big(p_i^N - \beta\,\mathbb{E}_i\,V_{N,i'}\Big)^{\eta}\Big(\beta\,\mathbb{E}_i\,H_{N,i'} - p_i^N - \beta\,\mathbb{E}_i\,B_{i'}\Big)^{1-\eta} \tag{1.58}$$

Free entry of buyers and sellers implies $B_i = 0$ and $V_{N,i} = k_i$, and as a result $\mathbb{E}_i\,B_{i'} = 0$ and $\mathbb{E}_i\,V_{N,i'} = \mathbb{E}_i\,k_{i'}$. The renovation threshold $\epsilon_{R,i}$ is calculated by

$$H_{R,i}(\epsilon_{R,i}) - k_i^R = H_{N,i} \tag{1.59}$$

As in the static case, equilibrium is defined by the joint solution to the system of value functions, free-entry conditions, the renovation threshold, and price equations. The resulting dynamic system consists of eleven equations in eleven unknowns, $\{\theta_i, \bar{p}_i^R, p_i^N \epsilon_{R,i}, \bar{\epsilon}_i, b_i, \phi_i, H_{N,i}, H_{R,i}(\epsilon_i), \bar{H}_{R,i}, V_{R,i}\}$, ensuring that a well-defined equilibrium exists in each state i.

1.4 Stylized Facts

This section documents new stylized facts on the cyclical co-movement between renovation activity and key housing market variables in the U.S. data. These empirical patterns motivate the role of renovation as a margin shaping housing market dynamics and serve as the targets against which the calibrated model is evaluated in Section 1.5.

1.4.1 Data

For the empirical analysis, I use aggregate national-level data on key housing market variables. To capture cyclical properties, all series are detrended using the Hodrick–Prescott filter with smoothing parameter 100, appropriate for annual data. Vacancies are measured using the Housing Vacancy Survey ("for sale only") from the U.S. Census Bureau and the U.S. Department of Housing and Urban Development (1963–2024). House prices are measured by the Median Sales Price for New Houses Sold in the United States (1963–2024). Sales are measured by the New One Family Houses Sold: United States series (1963–2024) from the Federal Reserve Economic Data. Time-on-market (TOM) is measured by the Median Number of Months on Sales Market for Newly Completed Homes (1975–2024) from the U.S. Census Bureau. Renovation activity is measured by the U.S. Bureau of Economic Analysis series on Private Fixed Investment in Residential Improvements (1929–2023). The sample spans the longest available period that is common across all five series.

Figure 1.2 plots the cyclical components of renovation activity together with each of the four housing market variables, and Table 1.1 reports the corresponding elasticities, correlations, and volatilities. Renovation activity co-moves positively with prices, vacancies, and sales, and negatively with time-on-market. Quantitatively, the elasticity of prices with respect to renovation is 0.37, the elasticity of time-on-market is -0.83, the elasticity of vacancies is 1.03, and the elasticity of sales is 0.93. Renovation also exhibits the highest volatility among all variables. The remaining cross-variable correlations are broadly consistent with prior search-and-matching studies of the housing market: prices, vacancies, and sales co-move positively, while time-on-market is negatively related to both vacancies and sales, as in Diaz and Jerez (2013) and Gabrovski and Ortego-Marti (2019). These empirical co-movements provide the targets against which the model is evaluated in Section 1.5.

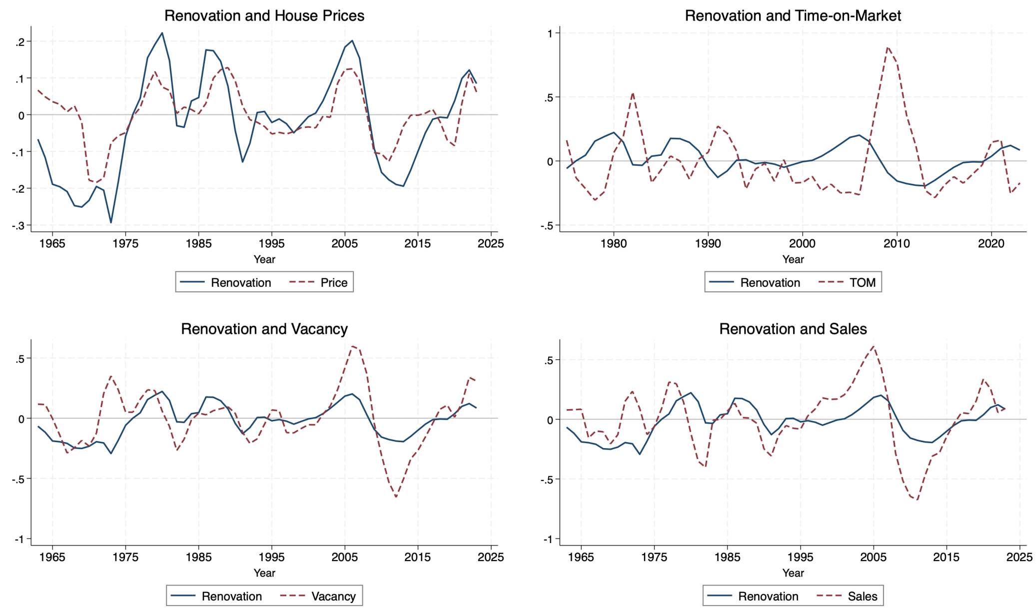


Figure 1.2: Cyclical co-movement of renovation with key housing market variables
Note. The figure plots the HP-filtered cyclical components of renovation activity (solid line) together with house prices, time-on-market, vacancies, and sales (dashed line) using U.S. aggregate annual data. The elasticity of price with respect to renovation is 0.37, the elasticity of time-on-market with respect to renovation is -0.83, the elasticity of vacancy with respect to renovation is 1.03, and the elasticity of sales with respect to renovation is 0.93.

1.5 Quantitative Assessment

As is standard in the housing search literature (e.g., Diaz & Jerez, 2013; Head et al., 2014; Ngai & Sheedy, 2020; Novy-Marx, 2009), I incorporate both demand and supply shocks to generate movements in prices and time-on-market. Specifically, the model features shocks to (i) aggregate housing utility x (demand), (ii) construction costs k (supply), and (iii) renovation costs k^R (renovation). To discipline the size of

Table 1.1: Empirical elasticities, correlations, and standard deviations

	Renovation	Price	TOM	Vacancy	Sales
Renovation	1.00				
Price	0.37	1.00			
TOM	−0.83	−0.10	1.00		
Vacancy	1.03	0.14	−0.28	1.00	
Sales	0.93	0.33	−0.62	0.59	1.00
Std. dev. (%)	31.10	7.49	26.61	24.18	26.09

Note. The table reports empirical elasticities, correlations, and standard deviations using HP-filtered U.S. aggregate annual data. Entries below the diagonal are elasticities; the entry in row i, column j is the elasticity of variable i with respect to variable j, computed as $E_{i,j} = \rho_{i,j}\, \sigma_i/\sigma_j$, where $\rho_{i,j}$ is the correlation between i and j and σ denotes the standard deviation of the HP-filtered log series. The diagonal entries equal one by construction. Standard deviations are reported in percent.

these shocks, I first calibrate the model to the U.S. economy and infer the shocks x, k, and k^R that match observed housing market volatility

To build intuition, I begin with the model's steady state behavior before turning to stochastic fluctuations. Following Ngai and Sheedy (2020) and Gabrovski and Ortego-Marti (2021b), I compute steady state elasticities of key variables. In search models, these elasticities provide a local measure of the model's response to innovations (see Shimer, 2005).

1.5.1 Calibration

The model is calibrated at a yearly frequency. The discount factor β is 0.9434 in order to match an annual interest rate 6%, Ngai and Tenreyro (2014). The utility of homeownership x is normalized to 1. As in Ngai and Tenreyro (2014), the bargaining power η is set to 0.5. The annual destruction rate δ equals 0.016 to match an annual housing depreciation rate of 1.6% (Van Nieuwerburgh and Weill (2010)). As in Diaz and Jerez (2013), I target an average tenure in a home of 9 years, which gives an s equal to 0.0951. For analytical convenience, the downgrade rate σ is set to equal to s, so that the expected duration of a renovated state is comparable in magnitude to the expected holding period. I impose a standard Cobb-Douglas matching function $m(\theta) = min\{\kappa\theta^{-\zeta}, 1\}$. The matching function elasticity for the housing market ζ is set to 0.5 following the evidence in Ngai, Iglhaut, Sheedy, Wu, and Zhang (2026). The elasticity of $c^B(b)$ with respect to the measure of buyers γ is 2 and I normalize $\bar{c} = 1$. The renovation cost k^R is set to 20% of the price. I target an annual frequency of renovation activity of 5% based on recent data.[9] To match this target, I set the Pareto tail parameter $\alpha = 2.34$, which controls the dispersion of match specific utility and thus the thickness of the upper tail of renovation opportunities. The parameter $\lambda = 0.24$ captures the arrival rate of renovation opportunities, governing how frequently homeowners face the option to undertake a renovation.

The U.S. Bureau of the Census reports that the average Median Number of Months on Sales Market for 1975-2024 was 5.05 months, which corresponds to 0.4208 years. This implies a sale hazard $= \log(2)/0.4208 = 1.65$, corresponding to an annual sale probability of $\theta m(\theta) = 1 - e^{-1.65} = 0.807$. As in Gabrovski and Ortego-Marti (2019), the average time-to-buy is set to the average time-to-sell. I follow Ghent (2012) and set the seller's expected search cost to 5.1% of the price and the buyer's expected search cost to 8% of the housing price.

[9] According to the 2019–2021 American Housing Survey (AHS), 59% of homeowners reported at least one home improvement project over a two year window, corresponding to an annual rate of roughly 30–35%. The Harvard Joint Center for Housing Studies (JCHS) similarly reports that 29.7% of homeowners completed at least one improvement project in both 2021 and 2023 from Improving America's Housing 2025. In addition, JCHS expenditure data indicate that about 30% of total improvement spending is devoted to major projects such as kitchen or bathroom remodels and room additions. Combining these figures suggests that approximately 8% of households undertake a major renovation each year. Because empirical definitions of major renovation vary across data sources, and because the model focuses on high cost renovation amounting to 20% of the house price, I target a conservative annual renovation rate of 5% in the baseline calibration.

A single aggregate shock induces fluctuations in homeownership utility x, construction costs k, and renovation costs k^R. Following Shimer (2005), I assume that a single underlying stochastic process drives all three shocks, so they are perfectly correlated. Under this assumption, the state of the economy can be summarized by a single index. During a hot market, a positive demand shock raises the utility of homeownership. This higher demand is accompanied by an increase in construction costs k, while renovation costs k^R also rise because both activities rely on the same inputs, such as labor and materials. Intuitively, strong housing demand increases the use of these inputs in both construction and renovation, pushing costs upward. My calibration therefore follows Gabrovski and Ortego-Marti (2019), who also assume that demand and supply shocks move together and are perfectly correlated.

I model $\ln(x)$, $\ln(k)$, and $\ln(k^R)$ as AR(1) processes driven by the same underlying shock u_t:

$$\ln(x_t) = \xi_x + \rho \ln(x_{t-1}) + u_t, \tag{1.60}$$

$$\ln(k_t) = \xi_k + \rho \ln(k_{t-1}) + a_k u_t, \tag{1.61}$$

$$\ln(k_t^R) = \xi_{k^R} + \rho \ln(k_{t-1}^R) + a_{k^R} u_t. \tag{1.62}$$

To simulate the model, I discretize the AR(1) processes using the method of Rouwenhorst (1995). Following the results of Kopecky and Suen (2010), this approach delivers more accurate approximations than the method of Tauchen (1986), especially for highly persistent processes. Each process is approximated by a five state Markov chain. The transition matrix is constructed using the autocorrelation coefficient $\rho = 0.9859$, which matches the empirical autocorrelation of house prices.

Table 1.2: Transition matrix

		To state				
		1	2	3	4	5
From state	1	0.9721	0.0276	0.0003	0.0000	0.0000
	2	0.0069	0.9722	0.0207	0.0001	0.0000
	3	0.0000	0.0138	0.9723	0.0138	0.0000
	4	0.0000	0.0001	0.0207	0.9722	0.0069
	5	0.0000	0.0000	0.0003	0.0276	0.9721

Note: Transition matrix for the stochastic shocks using Rouwenhorst (1995) method. The stationary distribution corresponding to Rouwenhorst transition matrix is [0.0625, 0.25, 0.375, 0.25, 0.0625].

The standard deviation of the shock is set to $\sigma_u = 0.18$, chosen to replicate the observed standard deviation of house prices.[10] The sensitivity parameters are $a_k = 1.84$ and $a_{k^R} = 2.71$, calibrated to match the elasticities of price, time-on-market, vacancy, and sales with respect to renovation. Steady state values imply $\ln(x) = 0$ and thus $\xi_x = 0$, $\ln(k) = 3.4497$ with $\xi_k = 0.5887$, and $\xi_{k^R} = 0.0118$. Table 1.2 reports the transition matrix implied by the Rouwenhorst discretization of the AR(1) process. The stationary distribution is symmetric, with most probability mass concentrated around the middle state, consistent with the persistence of the underlying shock. I simulate the model 1,000 times, with each run covering 60 years. Following standard practice, the first 20 simulated observations are discarded as a burn-in period to allow the process to converge to its stationary distribution and to eliminate dependence on initial conditions.

Table 1.3 summarizes the parameter values used in the baseline calibration. The parameters are divided into two groups. Externally calibrated parameters are disciplined directly by existing empirical studies or standard values in the housing search

[10]Assuming the price series follows an AR(1) process, $\sigma_u = \sqrt{1-\rho^2} \cdot sd[\ln(p)]$ with $sd[\ln(p)] = 0.074$ and $\rho = 0.98$.

Table 1.3: Calibrated parameters

Parameter	Value	Source / Target
A. Externally calibrated parameters		
Discount factor, β	0.943	6% annual interest rate Ngai and Tenreyro (2014)
Depreciation rate, δ	0.016	Van Nieuwerburgh and Weill (2010)
Matching elasticity, ζ	0.5	Ngai et al. (2026)
Bargaining power, η	0.5	Gabrovski and Ortego-Marti (2019)
Elasticity of buyer cost, γ	2	Gabrovski and Ortego-Marti (2021b)
Flow utility of housing, x	1	Normalization
Minimum match quality, ϵ_{min}	1	Normalization
B. Internally calibrated parameters		
Separation rate, s	0.0951	Average tenure = 9 years
Renovation cost, k^R	7.32	20% of average price
Construction cost, k	23.15	HE condition
Renovated house utility, μ	2.9	RC condition
Seller search cost, c^V	1.51	5.1% of price
Buyer search cost, c^B	2.36	8% of price

Notes: Externally calibrated parameters are disciplined directly by the data or existing literature. Internally calibrated parameters are jointly determined by the steady state equilibrium conditions.

literature. These include the discount factor, depreciation rate, matching elasticity, bargaining power, and search cost elasticity, which are set to ensure consistency with well established estimates. The remaining parameters are calibrated internally to satisfy the steady state equilibrium conditions of the model. In particular, the separation rate is chosen to match an average owner occupied housing tenure of nine years. The renovation cost is set to 20% of the average house price, while buyer and seller search costs are calibrated to represent approximately 8% and 5.1% of the transaction value, respectively. The construction cost is pinned down by the housing entry condition (HE), ensuring free entry of new housing supply in steady state.

Table 1.4 reports the baseline steady state equilibrium of the model. First, the model matches the empirical median time on market of 5.05 months, corresponding to 0.4208 years. This target pins down the sale hazard $\theta m(\theta)$. With market tightness normalized to $\theta = 1$, the implied meeting probability is $\theta m(\theta) = 0.807$. The associated steady state sales volume is $b\,m(\theta) = 8.24$, which implies an annual turnover rate of approximately $b\,m(\theta)/h = 0.16$ given the total owner occupied housing stock $h = 52.29$. Second, the model generates a sizable renovation premium in equilibrium. Non renovated houses sell for $p^N = 25.83$, while renovated houses sell for $p^R = 41.48$, implying a price premium of about 61%. This premium arises endogenously from the renovation threshold: only households drawing sufficiently high match-specific utility choose to renovate, and they incur renovation costs k^R in doing so. When these homes are subsequently sold, buyers value the higher match quality, while sellers recover both the renovation cost and part of the surplus generated by the improved match. As a result, renovated houses command a significantly higher price in equilibrium. This mechanism provides a natural explanation for the renovation premium observed in the data and justifies the presence of two distinct price levels in the model. The renovation condition pins down the renovation cutoff at $\epsilon_R = 1.19$. Given the Pareto distribution of match quality, this cutoff implies a tail mass of $1 - G(\epsilon_R) = 0.665$, so that roughly two thirds of match draws are renovation eligible when a renovation opportunity arrives. Third, the joint determination of the renovation threshold and market composition implies a quantitatively plausible renovation rate. In steady state, the flow of renovations is given by $\lambda\Big(1 - G(\epsilon_R)\Big)h^N$, so that the renovation rate as a share of the total housing stock is $\lambda\Big(1 - G(\epsilon_R)\Big)h^N/h = 0.05$ under the baseline calibration. As mentioned in Section 2.3.2, the model targets the moment of an annual renovation rate of 5%. Over time, renovation induces a steady state composition in which renovated houses account for the majority of the stock ($h^R/h = 0.69$), while only about 12% of active listings are non renovated ($\phi = 0.12$), which is consistent with the data.[11] This endogenous composition effect is a key channel through which renovation shapes the joint behavior of prices and market liquidity. Overall, the baseline calibration delivers a steady state that matches key empirical targets for time on market and market composition, while generating a renovation premium. This equilibrium provides a credible benchmark against which the model's comparative statics and shock propagation are studied in the next section.

Table 1.4: Baseline steady state equilibrium.

Variable	Equilibrium value
Average house price, $\bar{p}$	36.61
Non-renovated house price, p^N	25.83
Renovated house price, p^R	41.48
Market tightness, θ	1
Renovation threshold, ϵ_R	1.19
Sale hazard, $\theta m(\theta)$	0.807
Sales volume, $b\, m(\theta)$	8.24
Share of non-renovated listings, ϕ	0.119

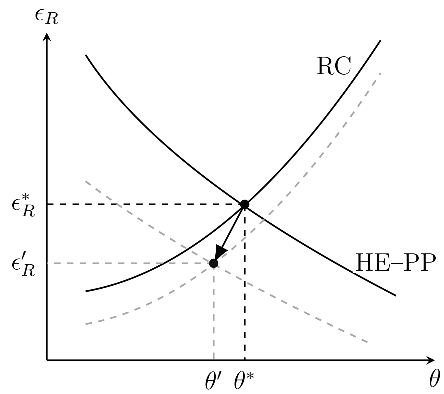
1.5.2 Comparative statics

Section 1.5.3 introduces business cycle fluctuations generated by multiple shocks. As shown in previous studies such as Diaz and Jerez (2013), Head et al. (2014, 2016),

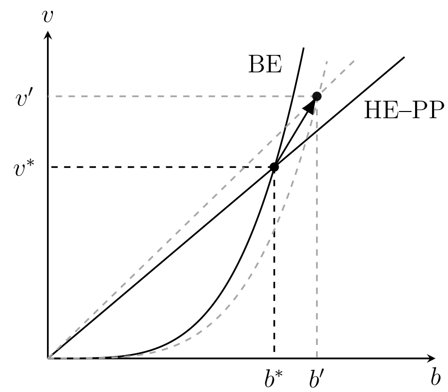
[11] Existing home sales account for the vast majority of residential transactions in the United States. According to the National Association of Realtors, existing home sales stood at about 4.10 million annualized units in late 2025, compared with typical new home sales around 0.7–0.8 million units according to U.S. Census Bureau data.

and Gabrovski and Ortego-Marti (2019), replicating key housing market dynamics requires the presence of aggregate shocks. To build intuition for the business cycle mechanism, this section examines the effects of each shock in isolation by analyzing their impact on the steady state equilibrium. A demand shock is modeled as an increase in x, which raises the utility flow from owning a home and strengthens households' incentives to purchase. Supply shocks take the form of increases in k, while renovation cost shocks correspond to increases in k^R. The analysis below highlights that vacancies and buyers respond in the same direction to each shock. This joint movement plays a key role in allowing the model to replicate the stylized facts once multiple shocks are combined in the calibration.

Demand shock. Consider a positive demand shock, modeled as an increase in x, which raises the flow utility of homeownership. Figure 1.3 illustrates these effects graphically. In Panel A, higher x makes renovation more attractive, shifting the RC curve downward so that a lower threshold ϵ_R is sufficient to trigger renovation. At the same time, the increase in total surplus stimulates entry on both sides of the market, shifting the HE–PP curve downward. The response of sellers, however, dominates: vacancies increase more than buyer inflows. For a given number of buyers, sellers post more vacancies, reflecting their willingness to tolerate lower market tightness when compensated by higher prices. Consequently, market tightness $\theta = b/v$ declines even as overall activity expands. The new equilibrium is therefore characterized by both a lower renovation threshold and lower market tightness. Panel B depicts the joint response of buyers and vacancies. The decline in equilibrium tightness rotates the HE–PP curve to the left. At the same time, higher prices and an increase in $m(\theta)$ raise buyer entry for any given vacancy level, shifting the BE curve to the right. As a result, both vacancies and buyers increase in equilibrium. Intuitively, lower market tightness improves buyers' matching prospects, which stimulates buyer entry.



(a) Response of equilibrium renovation threshold ϵ_R^* and market tightness θ^* to a utility shock



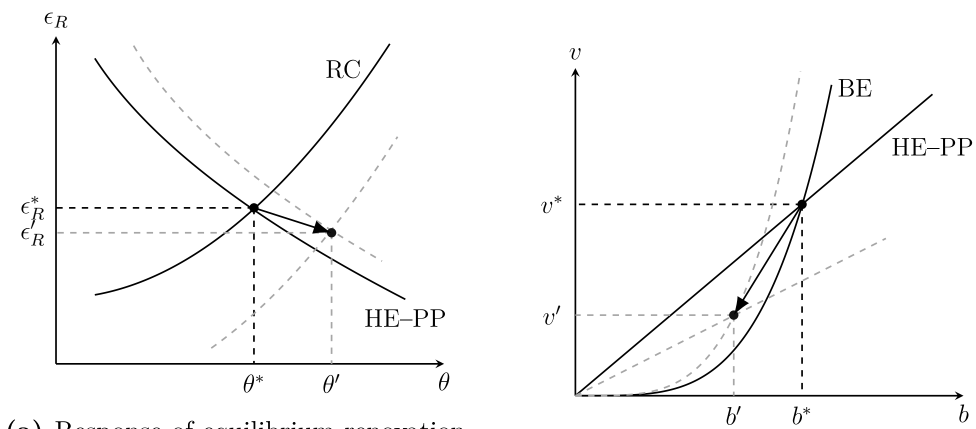
(b) Response of equilibrium buyer b^* and vacancies v^* to a utility shock

Note. *(Left)* An increase in x raises the net utility of homeownership, increasing matching surplus and equilibrium prices. Higher utility stimulates renovation activity, lowering the renovation threshold ϵ_R and shifting the RC curve downward, while stronger seller entry reduces market tightness and shifts the HE–PP curve downward. *(Right)* Lower market tightness improves buyers' matching probabilities, while higher prices encourage seller entry, resulting in an increase in both buyers and vacancies.

Figure 1.3: Comparative statics: demand shock

Supply shock. I next consider a supply shock, modeled as an increase in construction costs k. Higher construction costs reduce profitability and discourage seller entry, shifting the HE–PP curve upward in Panel A of Figure 1.4. For a given number of buyers, fewer sellers enter the housing market, leading to a decline in vacancies. At the same time, reduced seller entry tightens the housing market, lowering time-on-market and increasing the expected payoff from listing a house. This improves homeowners' incentives to renovate, shifting the RC curve downward: homeowners enjoy higher housing services while occupying the renovated home and can also expect to benefit from selling it at better market conditions upon separation. As a result, higher construction costs slow vacancy inflows relative to buyer inflows, leading to higher market tightness. In equilibrium, the combined movements of the two curves result in a lower renovation threshold and higher market tightness. Panel B illustrates the response of buyers and vacancies. The increase in market tightness flattens the

HE–PP curve. Given higher θ and higher k, the BE curve shifts leftward, leading to declines in both vacancies and buyers, v and b. Intuitively, higher market tightness reduces buyers' surplus and weakens their incentives to enter the housing market.



(a) Response of equilibrium renovation threshold ϵ_R^* and market tightness θ^* to a supply shock

(b) Response of equilibrium buyer b^* and vacancies v^* to a supply shock

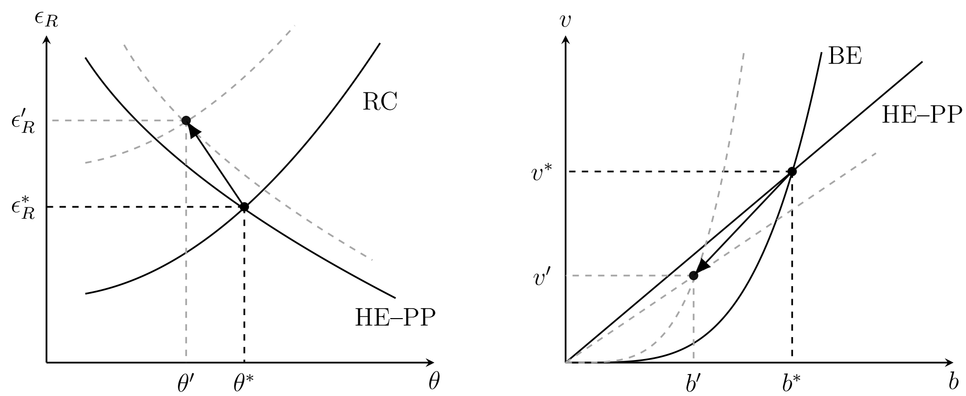
Note. *(Left)* A higher construction cost discourages seller entry, shifting the HE–PP curve upward. This raises the relative attractiveness of renovation, shifting the RC curve downward. The new equilibrium features a lower renovation threshold ϵ_R and higher market tightness θ. *(Right)* Higher market tightness reduces buyers' net surplus and entry. Both buyers and vacancies decline, with vacancy inflows contracting more rapidly.

Figure 1.4: Comparative statics: supply shock

Renovation cost shock. Lastly, I consider a renovation cost shock, modeled as an increase in k^R. Panel A of Figure 1.5 illustrates these effects. Higher renovation costs reduce the attractiveness of renovation, raising the renovation threshold ϵ_R and shifting the RC curve upward. At the same time, higher renovation costs increase the prices of renovated houses and, through the embedded option value of renovation, raise the average market price.[12] Higher market prices reduce buyers' surplus and weaken their incentives to enter the housing market. From the sellers' perspective, the decline in buyer entry lowers matching probabilities, which discourages seller entry as well. Together, these forces shift the HE–PP curve to the right, resulting

[12]When a buyer purchases a non-renovated house, the option value of renovation is embedded in the price. As renovation costs rise, this option becomes less valuable, reducing buyers' net surplus.

in a decline in market tightness. In equilibrium, the renovation threshold increases while market tightness falls.[13] Panel B shows the response of buyers and vacancies. The decline in market tightness rotates the HE–PP curve to the right. Given lower θ, the BE curve shifts leftward, leading to declines in both buyers and vacancies.



(a) Response of equilibrium renovation threshold ϵ^*_R and market tightness θ^* to a renovation cost shock

(b) Response of equilibrium buyer b^* and vacancies v^* to a renovation cost shock

Note. *(Left)* An increase in renovation costs reduces the attractiveness of renovation, shifting the RC curve upward and raising the renovation threshold ϵ_R. Because renovation costs are capitalized into house values, equilibrium house prices increase. Higher prices reduce buyer entry, while vacancy inflows decline more gradually, shifting the HE–PP curve to the right and lowering market tightness θ. *(Right)* Both buyers and vacancies decline, with buyer entry contracting more sharply. As a result, market tightness falls.

Figure 1.5: Comparative statics: renovation cost shock

An important distinction between renovation cost and construction cost shocks lies in their effects on market tightness. Although both shocks reduce buyer and seller entry, renovation cost shocks primarily operate through a reduction in buyers' surplus, causing buyer entry to fall more sharply and market tightness to decline. In contrast, construction cost shocks directly raise sellers' entry costs, leading vacancies

[13]The effect of a renovation cost increase on seller entry is, in principle, ambiguous. While lower market tightness reduces matching probabilities, higher prices may partially compensate sellers by allowing them to tolerate slower sales. In the calibrated economy, numerical exercises indicate that renovation cost shocks lead to declines in both buyer and seller entry, with buyer entry responding more strongly.

to contract more rapidly than buyers. As a result, market tightness increases following a construction cost shock but decreases following a renovation cost shock.

Overall, these comparative statics exercises show that vacancies and buyers respond in the same direction to each shock, while the response of market tightness varies by shock type. Demand shocks lower market tightness through stronger seller entry, supply shocks raise it by tightening housing supply, and renovation cost shocks lower it by suppressing buyer entry. Combining demand, supply, and renovation cost shocks therefore allows the calibrated model to match the observed cyclical comovements documented in Section 1.4, as shown in Section 1.5.3.

1.5.3 Results

This section evaluates the calibrated model's ability to reproduce the empirical comovements documented in Section 1.4. To highlight the role of renovation, I additionally simulate two counterfactual economies. The No Renovation specification shuts the channel down entirely, while the Exogenous Renovation specification keeps the channel active but holds renovation activity at its steady-state level so that it cannot respond to the cycle. Together, the two counterfactuals isolate distinct dimensions of the renovation mechanism.

Before presenting the main simulation results, I assess the model's external validity by examining the elasticities of prices with respect to time-on-market, vacancies, and sales, which serve as important benchmarks for evaluating model performance. These elasticities have been widely used as calibration targets in the literature, so the model's ability to reproduce them provides an additional validation of its underlying mechanisms. The model replicates the empirical relationships qualitatively, generating the correct signs across all three margins. In particular, it captures the

Table 1.5: Results: baseline model and counterfactuals

Elasticity of X wrt Renovation	Data	Model	No Renovation	Exogenous Renovation
Price, $E_{p,R}$	0.37	0.37	—	1.72
Time-on-market, $E_{tom,R}$	−0.83	−0.98	—	−4.01
Vacancy, $E_{vacancy,R}$	1.03	0.67	—	1.41
Sales, $E_{sales,R}$	0.93	0.81	—	1.69
Elasticity of Price wrt X	**Data**	**Model**	**No Renovation**	**Exogenous Renovation**
TOM, $E_{p,tom}$	−0.10	−0.05	−0.08	−0.06
Vacancy, $E_{p,vacancy}$	0.14	0.55	0.12	1.22
Sales, $E_{p,sales}$	0.33	0.46	0.07	1.01

Note. Data reports the empirical moments. Model reports the baseline calibration with endogenous renovation decisions. No Renovation reports the counterfactual in which the renovation channel is shut down entirely; renovation-related elasticities are undefined by construction (—). Exogenous Renovation reports the counterfactual in which the renovation threshold ϵ_R and the flow of renovating households are held at their steady-state values, so that renovation activity does not respond to the cycle.

upward-sloping Beveridge curve documented by Gabrovski and Ortego-Marti (2019). The positive elasticity of prices with respect to vacancies implies that buyers and vacancies move together, consistent with observed co-movement in housing markets. Table 1.5 reports the results. Quantitatively, the elasticity of prices with respect to time-on-market is −0.05 in the model, compared with −0.10 in the data, while the corresponding elasticities with respect to vacancy and sales are 0.55 and 0.46, respectively, versus 0.14 and 0.33 in the data. The model captures the signs and the broad pattern of co-movement, although the magnitudes of the responses of vacancies and sales to prices exceed those in the data. The counterfactual exercises below help interpret this pattern by isolating the contribution of the renovation channel.

I now turn to the main results, which focus on the stylized facts explicitly targeted in the simulations. Column 2 of Table 1.5 reports the elasticities of prices, time-on-market, vacancies, and sales with respect to renovation. The model delivers an excellent quantitative fit across all dimensions. In particular, the elasticity of prices with respect to renovation is 0.37 in both the model and the data. Similarly, the elasticities of time-on-market, vacancies, and sales are −0.98, 0.67, and 0.81 in the model, compared with −0.83, 1.03, and 0.93 in the data. Overall, the baseline calibration closely matches the central empirical moments, confirming that the model successfully captures the key co-movement between renovation activity and housing market dynamics. The calibrated model's response to an aggregate shock follows the dynamics derived in Section 1.5.2. A positive demand shock raises buyers' surplus, prices, and renovation activity, while the associated increase in construction and renovation costs reduces sellers' surplus and tightens the market. Under the calibrated parameters, these forces combine to deliver procyclical movements in prices, vacancies, sales, and renovation activity, and countercyclical movements in time-on-market, consistent with the data.

I now compare the baseline model with the two counterfactual specifications that isolate distinct aspects of the renovation channel. The No Renovation counterfactual shuts the channel down entirely, so that non-renovated homeowners never draw an opportunity to renovate and separating homeowners list the house as-is. The renovated stocks then vanish, $h^R = v^R = 0$, and the entire market consists of non-renovated houses.[14] The Exogenous Renovation counterfactual instead keeps the channel active

[14]Since the renovation cost shock k^R has no role in this specification, I replace it with a separation rate shock to preserve a second source of supply-side variation, ensuring that the comparison with the baseline isolates the role of the renovation channel rather than the number of underlying shocks. Specifically, the separation rate shock s_t follows an AR(1) process driven by the same underlying innovation u_t as in the baseline, with sensitivity a_s. The sensitivity parameters a_k and a_s are recalibrated to match the empirical elasticity of prices with respect to time-on-market ($E_{p,tom} = -0.10$).

but holds the renovation threshold and the flow of renovating households at their steady-state values, so that renovation activity does not respond to the cycle.

The No Renovation specification recovers the qualitative pattern of the standard housing search model.[15] Column 3 of Table 1.5 shows that prices and vacancies co-move positively, while time-on-market and vacancies co-move negatively, both consistent with the data.[16] Quantitatively, the model reproduces the elasticity of prices with respect to time-on-market closely (-0.08 in the model versus -0.10 in the data), and the elasticity of prices with respect to vacancies (0.12 versus 0.14). The positive price-vacancy relationship implies that the No Renovation specification successfully replicates the upward-sloping Beveridge curve, confirming that the model nests a well-behaved standard search environment as a special case. The response of sales relative to prices, however, is much larger than in the data (0.07 versus 0.33), indicating that without the renovation channel, sales fluctuate excessively relative to prices. With endogenous renovation, the corresponding elasticity is 0.46, closely matching the data. The Exogenous Renovation specification (Column 4 of Table 1.5) generates the opposite pattern. When renovation activity is constrained to remain at its steady-state level, vacancies and sales fluctuate more than in the data in response to prices (1.22 and 1.01, respectively), indicating that the remaining margins of adjustment, buyer and seller entry, must absorb the entire shock. The same pattern appears in the elasticities of housing market variables with respect to renovation. The model under Exogenous Renovation generates values of 1.72, -4.01, 1.41, and 1.69 for the

[15] The reduced model corresponds to the single-type housing search environment of Gabrovski and Ortego-Marti (2019), with one homeowner Bellman equation, one seller Bellman equation, a single price determined by Nash bargaining, and free-entry conditions for buyers and sellers.

[16] Following Gabrovski and Ortego-Marti (2019), I interpret the elasticities of prices with respect to housing market variables as regression coefficients. A smaller elasticity indicates that the housing market variable is more volatile relative to prices, while a larger elasticity indicates that prices respond more strongly to the variable. The empirical pattern, that sales, vacancies, and time-on-market are much more volatile than prices, is therefore reflected in elasticities below one.

elasticities of prices, time-on-market, vacancies, and sales, which are large relative to their empirical counterparts of 0.37, −0.83, 1.03, and 0.93. Endogenous renovation therefore operates as an adjustment margin alongside buyer and seller entry, allowing housing market variables to respond to aggregate shocks in line with the data.

These results naturally raise the question: does renovation amplify or dampen housing cycles? In their broader survey of housing and credit cycles, Duca et al. (2021) cite Bogin and Doerner (2019) in noting that renovation activity is concentrated in housing booms and in high-cost areas. Their discussion, however, is framed primarily in terms of measurement bias in repeat-sales price indices, and does not formally analyze how renovation interacts with housing market dynamics. By embedding renovation as an endogenous decision margin within a search and matching framework, the present paper provides the first equilibrium framework in which this question can be analyzed quantitatively. The analysis shows that endogenous renovation is a quantitatively important margin of adjustment in the housing market, and that housing market variables track the cyclical behavior observed in the data only when this margin is allowed to respond endogenously.[17] Overall, these results highlight renovation as an important channel of housing market dynamics.

1.6 Conclusion

This paper develops a search and matching model of the housing market that incorporates an explicit renovation channel. Using aggregate U.S. data, I document new stylized facts showing that renovation activity is positively related to prices, vacancies,

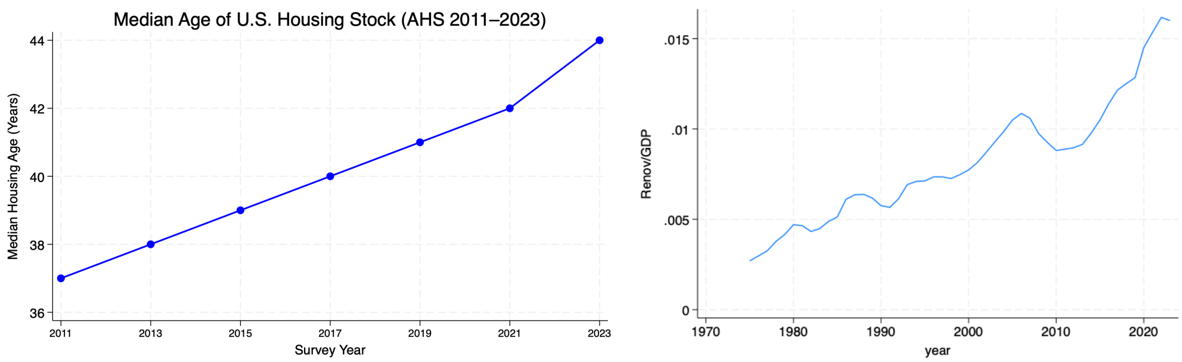
[17] Whether the renovation channel ultimately amplifies or dampens housing cycles depends on the comparison being made and on which margins of the housing market are held fixed. The present paper does not take a stand on this question. What the analysis identifies is the role of the renovation margin in housing market dynamics: abstracting from this margin pushes the cyclical behavior of housing market variables away from the data.

and sales, and negatively related to time-on-market. To account for these patterns, the model features endogenous renovation decisions by homeowners. The calibrated model replicates the targeted elasticities both qualitatively and quantitatively. Two counterfactual exercises further clarify the role of the renovation channel. The No Renovation specification confirms the model's validity by recovering the qualitative pattern of the standard housing search model as a special case. The Exogenous Renovation specification, in turn, shows that the endogenous response of renovation activity is what allows housing market variables to track the cyclical behavior observed in the data: when renovation is held fixed, the remaining margins of adjustment overreact to aggregate shocks. While prior studies on renovation have noted that renovation is procyclical and warrants further investigation, the question of how the renovation channel interacts with housing market fluctuations has not previously been addressed in a structural search model. The analysis in this paper provides the first quantitative assessment of this channel within a formal equilibrium framework, highlighting renovation as an important channel of housing market dynamics.

Several extensions remain for future research. One natural direction is to incorporate a credit market to study how financial frictions shape the interaction between renovation and housing market activity. As in the housing market, the credit market is subject to search frictions, where financial intermediaries must match with borrowers, and borrowers must find suitable lenders. These interactions jointly determine housing outcomes. Another extension is to introduce renovation-related policies such as the Inflation Reduction Act enacted in 2022 to evaluate how environmental incentives affect renovation activity and housing market outcomes. By linking renovation to broader environmental objectives, such policies make renovation an increasingly important component of housing investment. Incorporating taxes, rebates, and regulatory constraints would also enable welfare analysis across alternative policy environments. Overall, these extensions would provide a richer understanding of how renovation interacts with housing and credit markets and deepen insight into its role in shaping housing market dynamics.

Appendix

A. Additional Evidence on Housing Age and Renovation



(a) Median Housing Age (b) Ratio of Renovation Expenditure to GDP

Note. The left panel reports the median age of the U.S. housing stock. The right panel shows aggregate renovation expenditures as a share of GDP. These figures illustrate the growing importance of renovation over time. *Source:* Median housing age from the American Housing Survey. Renovation expenditures and GDP from the Bureau of Economic Analysis.

Figure 1.6: Housing Age and Ratio of Renovation to GDP

B. Robustness: Renovation Decision at Separation

This appendix examines the robustness of the main results to the assumption that all separating homeowners renovate before listing. In the baseline calibration, the parameter restriction $\beta V_R - k^R > \beta V_N$ implies that renovation at separation is strictly optimal as a corner solution. To assess whether this corner-solution simplification drives the main results, I consider two alternative specifications: (i) an *as-is* specification in which no separating homeowner renovates before listing; and (ii) a *mixed* specification in which only a small fraction of separating homeowners renovate before listing, calibrated to the share of homeowners who report renovating primarily in preparation for resale in the National Association of Realtors' *2025 Remodeling Impact Report* (see footnote 4). Across both alternatives, the qualitative pattern of the elasticities is unchanged; only the magnitudes differ.

As-Is Sale

This subsection examines the alternative specification in which a non-renovated homeowner sells the house *as-is* upon receiving a separation shock. In particular, we replace the separation payoff $\max\{\beta V_N, \beta V_R - k^R\}$ with βV_N, thereby ruling out renovation at the moment of separation. The Bellman equation for a non-renovated homeowner becomes

$$H_N = x + (1-\delta)\Big((1-s)\Big(\big(1-\lambda(1-G(\epsilon_R))\big)\beta H_N + \lambda\int_{\epsilon_R}(\beta H_R(\tau) - k^R)dG(\tau)\Big) + s\,\beta V_N\Big). \quad (1.63)$$

This equation can be rewritten as

$$H_N = \frac{x + (1-\delta)(1-s)\lambda(1-G(\epsilon_R))(\beta \bar{H}_R - k^R) + (1-\delta)s\,\beta k}{1-\beta(1-\delta)(1-s)\big(1-\lambda(1-G(\epsilon_R))\big)}. \quad (1.64)$$

Given this modified continuation value, the reduced-form expressions for V_R, $\bar{H}_R$, and H_N are

$$V_R = \frac{\tilde{\delta}\tilde{\eta}\,\bar{H}_R - c^V}{1-\tilde{\delta}(1-\tilde{\eta})}, \tag{1.65}$$

$$\bar{H}_R = \frac{x\mu\bar{\epsilon} - \dfrac{\tilde{\delta}(1-\tilde{s})c^V}{1-\tilde{\delta}(1-\tilde{\eta})} + \dfrac{\tilde{\delta}\tilde{s}\sigma}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}\,\Pi_x^{\text{as}}}{1-\tilde{\delta}\tilde{s}(1-\sigma) - \dfrac{\tilde{\delta}^2(1-\tilde{s})\tilde{\eta}}{1-\tilde{\delta}(1-\tilde{\eta})} - \dfrac{\tilde{\delta}\tilde{s}\sigma}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}\,\Pi_\eta^{\text{as}}}, \tag{1.66}$$

$$H_N = \frac{\Pi_x^{\text{as}} + \Pi_\eta^{\text{as}}\bar{H}_R}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}, \tag{1.67}$$

where $\tilde{\delta} \equiv \beta(1-\delta)$, $\tilde{s} \equiv 1-s$, $\tilde{\eta} \equiv \theta m(\theta)\eta$, $\tilde{\lambda} \equiv \lambda(1-G(\epsilon_R))$, $\Pi_x^{\text{as}} \equiv x - \tilde{\delta}\frac{\tilde{s}\tilde{\lambda}}{\beta}\,k^R + \tilde{\delta}(1-\tilde{s})k$, and $\Pi_\eta^{\text{as}} \equiv \tilde{\delta}\tilde{s}\tilde{\lambda}$. The price equation for non-renovated houses is correspondingly modified as

$$\text{(PPN):}\quad p^N = \beta\left[\left(\frac{\eta\Pi_\eta^{\text{as}}}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})}\right)\bar{H}_R + \frac{\eta\Pi_\eta^{\text{as}}}{1-\tilde{\delta}\tilde{s}(1-\tilde{\lambda})} + (1-\eta)k\right]. \tag{1.68}$$

Because h_t^N now flows into v_{t+1}^N upon separation, the law of motion for vacancies is given by

$$v_{t+1}^R = v_t^R + sh_t^R - \Big(\theta_t m(\theta_t)(1-G(\epsilon_{R,t})) + \delta\Big)v_t^R, \tag{1.69}$$

$$v_{t+1}^N = v_t^N + n_t + sh_t^N - \Big(\theta_t m(\theta_t) + \delta\Big)v_t^N. \tag{1.70}$$

Solving the system yields a modified expression for ϕ,

$$\phi = \frac{v(\theta m(\theta)[1-G(\epsilon_R)]+\delta)(\delta+s)(\delta+s+\lambda(1-G(\epsilon_R))+\sigma) - sbm(\theta)[1-G(\epsilon_R)](\delta+s+\lambda(1-G(\epsilon_R)))}{v(\theta m(\theta)[1-G(\epsilon_R)]+\delta)(\delta+s)(\delta+s+\lambda(1-G(\epsilon_R))+\sigma) - sbm(\theta)[1-G(\epsilon_R)](\delta+s-\lambda G(\epsilon_R))}. \tag{1.71}$$

Table 1.6: Robustness of Elasticities to the Renovation-at-Separation Decision

Elasticity of X wrt Renovation	Data	Baseline	As-Is	Mixed
Price, $E_{p,R}$	0.37	0.37	0.37	0.25
Time-on-market, $E_{tom,R}$	-0.83	-0.98	-0.87	-1.59
Vacancy, $E_{vacancy,R}$	1.03	0.67	0.82	0.79
Sales, $E_{sales,R}$	0.93	0.81	0.51	0.64
Elasticity of Price wrt X	**Data**	**Baseline**	**As-Is**	**Mixed**
TOM, $E_{p,tom}$	-0.10	-0.05	-0.05	-0.02
Vacancy, $E_{p,vacancy}$	0.14	0.55	0.44	0.32
Sales, $E_{p,sales}$	0.33	0.46	0.72	0.39

Note. The first column reports the empirical elasticities from Section 1.5. The remaining columns report model elasticities under three calibrations of the renovation-at-separation decision: *Baseline*, in which all separating homeowners renovate before listing; *As-Is*, in which no separating homeowner renovates before listing (Section 1.6); and *Mixed*, in which only a small fraction of separating homeowners renovate before listing, calibrated to the share reporting resale as the primary motivation in the National Association of Realtors' *2025 Remodeling Impact Report* (Section 1.6).

Numerical simulations show that this as-is specification continues to replicate the main stylized facts both qualitatively and quantitatively. In particular, the elasticities of prices, time-on-market, vacancies, and sales remain close to their empirical counterparts, as reported in Table 1.6 (*As-Is* column). However, ruling out renovation at separation significantly reduces the share of renovated houses in equilibrium. As a result, renovation activity becomes nearly constant, leading to extremely small variation in renovation rates. This mechanically inflates elasticities with respect to renovation, even though the underlying market dynamics remain similar. Importantly, under the calibrated parameters, the model satisfies $\beta V_N < \beta V_R - k^R$, implying that renovation at separation is strictly optimal. Consequently, allowing sellers to choose between listing a non-renovated or renovated house preserves optimality and better reflects the data. For this reason, the baseline specification adopts $\max\{\beta V_N, \beta V_R - k^R\}$ as the separation payoff. Nevertheless, the as-is specification delivers similar aggregate dynamics, indicating that the main results are robust to this modeling choice.

Mixed Specification

This subsection examines an intermediate specification in which only a small fraction of separating homeowners renovate before listing while the remaining majority list the house as-is. The fraction is calibrated to the National Association of Realtors' *2025 Remodeling Impact Report*, which reports that roughly 18% of homeowners undertake renovation primarily in preparation for resale (see footnote 4 of Section 1.1).

The results are reported in the fourth column of Table 1.6 (*Mixed*). All qualitative features of the baseline are preserved: the elasticities of price, vacancies, and sales with respect to renovation remain positive, the elasticity of time-on-market with respect to renovation remains negative, and the cyclical co-movements between price and the other housing market variables retain the same sign pattern observed in the data. The main quantitative implications of the model, namely that the renovation channel operates as an adjustment margin shaping the cyclical co-movement of prices, vacancies, sales, and time-on-market, hold throughout. The Mixed specification therefore confirms that the central findings of the paper are not driven by the corner-solution simplification adopted in the baseline.

C. Directed Search Model

This appendix extends the baseline model by replacing Nash bargaining with directed search. The purpose is to consider an environment in which the housing market is segmented into a renovated submarket and a non-renovated submarket, with buyers sorting across submarkets ex ante. Under directed search, sellers post prices before buyers enter the market, and each buyer chooses which submarket to enter after observing the posted price. Prices are therefore not determined through ex-post bargaining; instead, each seller chooses a posted price that trades off the transaction price against the market tightness induced by buyer entry. As shown below, the main results of the paper are robust to this alternative specification.

Environment

The economy consists of two submarkets: (i) renovated houses and (ii) non-renovated houses. Buyers observe the renovation status of a listed house before entering the market and choose which submarket to search in. Within each submarket, matching is random and governed by the same matching function as in the baseline model.

Let v_R and v_N denote the measures of renovated and non-renovated vacancies, and let b_R and b_N denote the measures of buyers searching in each submarket. Submarket tightness is

$$\theta_R \equiv \frac{b_R}{v_R}, \qquad \theta_N \equiv \frac{b_N}{v_N}.$$

The probability that a buyer finds a match in submarket $j \in \{R, N\}$ is $m(\theta_j)$, and the probability that a vacancy in submarket j is filled is $\theta_j m(\theta_j)$. Buyers in each submarket $j \in \{R, N\}$ incur a search cost $c^B(b_j) = \bar{c}\, b_j^{\gamma}$. This specification captures congestion effects within each submarket separately, consistent with the segmented market structure.

Bellman Equations

Homeowners. The renovation decision is made by homeowners before any search takes place and is therefore unaffected by the search protocol. The Bellman equations for renovated and non-renovated homeowners are identical to those in the baseline model:

$$H_R(\epsilon) = x\mu\epsilon + (1-\delta)\Big[(1-s)\Big((1-\sigma)\beta H_R(\epsilon) + \sigma\beta H_N\Big) + s\,\beta V_R\Big], \tag{1.72}$$

$$H_N = x + (1-\delta)\left[(1-s)\left((1-\lambda)\beta H_N + \lambda\int \max\Big\{\beta H_N,\, \beta H_R(\tau) - k_R\Big\} dG(\tau)\right) + s\,(\beta V_R - k_R)\right]. \tag{1.73}$$

To ensure that non-renovated homeowners optimally renovate before listing upon separation, we require $\beta V_R - k_R > \beta V_N$. The renovation threshold condition (1.74) below implies $\beta\bar{H}_R - \beta H_N > k_R$, since $\bar{H}_R = \mathbb{E}[H_R(\epsilon) \mid \epsilon \geq \epsilon_R] > H_R(\epsilon_R)$ by definition. Substituting the posted-price conditions (1.80)–(1.81) yields a sufficient condition $\bar{p}_R - p_N > k_R + \Big(c^B(b_R)/m(\theta_R) - c^B(b_N)/m(\theta_N)\Big)$, which holds whenever the search cost differential across submarkets is not too large. We verify numerically that this condition is satisfied under the calibrated parameters.

As in the baseline, renovation follows a threshold rule. The cutoff ϵ_R is defined by the indifference condition

$$\beta H_R(\epsilon_R) - k_R = \beta H_N, \tag{1.74}$$

so homeowners renovate if and only if $\epsilon \geq \epsilon_R$.

Sellers. Because match-specific utility ϵ is realized only after a buyer and seller are matched, the renovated seller posts a common price $\bar{p}_R$ based on the expected value of the house conditional on $\epsilon \geq \epsilon_R$. Define $\bar{p}_R \equiv \int_{\epsilon_R}^{\infty} p_R(\epsilon)\, dG(\epsilon)/(1 - G(\epsilon_R))$. The Bellman equations for renovated and non-renovated sellers are

$$V_R = -c^V + (1-\delta)\Big[\Big(1 - \theta_R m(\theta_R)\Big)\beta V_R + \theta_R m(\theta_R)\, \bar{p}_R\Big], \tag{1.75}$$

$$V_N = -c^V + (1-\delta)\Big[\Big(1 - \theta_N m(\theta_N)\Big)\beta V_N + \theta_N m(\theta_N)\, p_N\Big]. \tag{1.76}$$

Buyers. Under free entry, buyers enter each submarket until the value of search is zero. The Bellman equations for buyers in the renovated and non-renovated submarkets are

$$B_R = -c^B(b_R) + \Big(1 - m(\theta_R)\Big)\beta B_R + m(\theta_R) \int_{\epsilon_R}^{\infty} \Big(\beta H_R(\tau) - \bar{p}_R\Big) \frac{dG(\tau)}{1 - G(\epsilon_R)}, \tag{1.77}$$

$$B_N = -c^B(b_N) + \Big(1 - m(\theta_N)\Big)\beta B_N + m(\theta_N)\Big(\beta H_N - p_N\Big). \tag{1.78}$$

Free entry in each submarket drives $B_R = B_N = 0$, which immediately implies $\beta B_j = 0$ in equations (1.77)–(1.78).

Equilibrium

Free entry and the renovation threshold. Free entry of buyers drives $B_R = B_N = 0$. Free entry of non-renovated sellers requires $V_N = k$. The renovation threshold is determined by (1.74). Buyer indifference across active submarkets implies

$$\frac{c^B(b_N)}{m(\theta_N)} = \frac{c^B(b_R)}{m(\theta_R)}. \tag{1.79}$$

Pricing conditions. Applying $B_j = 0$ to equations (1.77)–(1.78) yields the posted-price conditions:

$$\bar{p}_R = \beta \bar{H}_R - \frac{c^B(b_R)}{m(\theta_R)}, \tag{1.80}$$

$$p_N = \beta H_N - \frac{c^B(b_N)}{m(\theta_N)}, \tag{1.81}$$

where $\bar{H}_R \equiv \int_{\epsilon_R}^{\infty} H_R(\epsilon)\, dG(\epsilon)/(1 - G(\epsilon_R))$. The posted price equals the buyer's expected homeownership value net of the expected search cost.

Seller's problem. Sellers post prices anticipating how they affect buyer entry and thereby submarket tightness. Substituting (1.80)–(1.81) into (1.75)–(1.76) and differentiating yields the first-order conditions:

$$\Big[1 + \Sigma(\theta_N)\Big]\Big(p_N - \beta V_N\Big) - \frac{\theta_N c^{B\prime}(b_N)\, v_N}{m(\theta_N)} + \Sigma(\theta_N)\,\frac{c^B(b_N)}{m(\theta_N)} = 0, \tag{1.82}$$

$$\Big[1 + \Sigma(\theta_R)\Big]\Big(\bar{p}_R - \beta V_R\Big) - \frac{\theta_R c^{B\prime}(b_R)\, v_R}{m(\theta_R)} + \Sigma(\theta_R)\,\frac{c^B(b_R)}{m(\theta_R)} = 0, \tag{1.83}$$

where $\Sigma(\theta) \equiv \theta m'(\theta)/m(\theta)$ is the elasticity of the matching function.

Laws of motion. The steady-state laws of motion are

$$h_R = \frac{b_R m(\theta_R) + \lambda(1 - G(\epsilon_R))h_N}{\delta + s + \sigma}, \tag{1.84}$$

$$h_N = \frac{b_N m(\theta_N) + \sigma h_R}{\delta + s + \lambda(1 - G(\epsilon_R))}, \tag{1.85}$$

$$v_R = \frac{s\Big(h_R + h_N\Big)}{\theta_R m(\theta_R) + \delta}, \tag{1.86}$$

$$v_N = \frac{n}{\theta_N m(\theta_N) + \delta}. \tag{1.87}$$

Equilibrium definition and characterization. A directed-search equilibrium is a tuple

$\Big\{\theta_R, \theta_N, b_R, b_N, v_R, v_N, h_R, h_N, \bar{H}_R, H_N, V_R, V_N, \bar{p}_R, p_N, \epsilon_R, n\Big\}$ satisfying: homeowner Bellman equations (1.72)–(1.73); seller Bellman equations (1.75)–(1.76); buyer free entry $B_R = B_N = 0$; seller optimality (1.82)–(1.83); buyer indifference (1.79); non-renovated seller free entry $V_N = k$; renovation cutoff (1.74); and the steady-state laws of motion (1.84)–(1.87), with $\theta_R = b_R/v_R$ and $\theta_N = b_N/v_N$.

Solving (1.72) yields

$$H_R(\epsilon) = \frac{x\mu\epsilon + \beta(1-\delta)(1-s)\sigma H_N + \beta(1-\delta)s\,V_R}{1-\beta(1-\delta)(1-s)(1-\sigma)}. \tag{1.88}$$

Taking expectations conditional on $\epsilon \geq \epsilon_R$ gives an analogous expression for $\bar{H}_R$. Substituting (1.80) into (1.75) gives

$$V_R = \frac{-c^V + (1-\delta)\theta_R m(\theta_R)\Big[\beta\bar{H}_R - c^B(b_R)/m(\theta_R)\Big]}{1-\beta(1-\delta)\Big[1-\theta_R m(\theta_R)\Big]}. \tag{1.89}$$

The renovation cutoff condition combined with (1.88) gives an explicit expression for ϵ_R.

Numerical Results

We now solve the directed-search model numerically and compare its predictions to the baseline. The strategy is twofold. First, we compute the equilibrium response to one-percent shocks in structural parameters and compare these to the random-search benchmark (Section 1.6). Second, we conduct the full business cycle simulation following the methodology of Section 1.5.3 of the main text, calibrating aggregate shocks to match the empirical elasticities of housing market variables with respect to renovation (Section 1.6).

Steady-State Comparative Statics

We first examine how the directed-search equilibrium responds to a one-percent increase in homeownership utility (x), construction costs (k), and renovation costs (k^R), and compare these to the baseline random-search responses.

To compare the two models on common ground, we aggregate submarket-level outcomes in the directed-search model. Aggregate vacancies and buyers are $v = v^R + v^N$ and $b = b^R + b^N$. Aggregate sales are $q = \theta^R m(\theta^R) v^R + \theta^N m(\theta^N) v^N$. The average transaction price is the homeowner-stock weighted average $\bar{p} = (h^R/(h^R + h^N))\,\bar{p}^R + (h^N/(h^R + h^N))\,p^N$, and aggregate renovation activity is $\mathcal{R} = \lambda(1 - G(\epsilon_R))h^N + s\,h^N$. Time-on-market is the vacancy-weighted average across submarkets, $\text{TOM} = (v^R\,\text{TOM}^R + v^N\,\text{TOM}^N)/(v^R + v^N)$, where $\text{TOM}_j = 1/[\theta_j m(\theta_j)]$.

Table 1.7: Comparative Statics: Percentage Change Following a 1% Shock

	Random Search			Directed Search		
Variable	$+1\%\,x$	$+1\%\,k$	$+1\%\,k^R$	$+1\%\,x$	$+1\%\,k$	$+1\%\,k^R$
Price	+0.30%	+0.56%	+0.12%	+0.57%	+0.36%	+0.08%
Sales	+0.76%	−0.12%	−0.03%	+1.22%	−0.64%	−0.09%
Time-on-Market	+1.17%	−0.67%	−0.01%	+1.12%	−0.82%	−0.18%
Vacancy	+1.45%	−0.63%	0.00%	+2.06%	−1.27%	−0.23%
Renovation	+0.57%	+0.02%	−0.15%	+1.17%	−0.55%	−0.17%

Note. Each entry reports the percentage change in the variable relative to the steady state following a one-percent increase in the indicated parameter. Random-search results are computed at the calibrated steady state of the baseline model. Directed-search results are computed at the directed-search steady state with the non-renovated vacancy stock normalized to $v^N = 1.5$, yielding sell probabilities $\theta^R m(\theta^R) = 0.645$ and $\theta^N m(\theta^N) = 0.806$.

The two protocols deliver the same qualitative pattern for prices, sales, vacancies, and time-on-market across all three shocks. The only qualitative discrepancy concerns the response of renovation activity to a supply shock: random search yields a marginal increase (+0.02%), while directed search yields a small decrease (−0.55%). The divergence arises from the free-entry condition $V^N = k$ that ties the non-renovated seller's outside option directly to construction costs in the directed-search environment, dampening the offsetting movement in ϵ_R that drives the random-search result. Under directed search, higher k contracts the non-renovated homeowner stock h^N, which mechanically reduces the pool eligible to renovate. This single difference reflects the distinct role construction costs play under each protocol—through Nash bargaining in random search versus through the free-entry condition $V^N = k$ in directed search—and represents a genuine, interpretable distinction rather than a failure of robustness.

Business Cycle Simulation

We now repeat the business cycle exercise of Section 1.5.3 under the directed-search protocol. Aggregate shocks to homeownership utility (x), construction cost (k), renovation cost (k^R), and separation rate (s) follow the same five-state Markov chain as in the baseline; their magnitudes are calibrated separately for the directed-search model to match four empirical elasticities (price, vacancy, sales, and time-on-market with respect to renovation activity). Simulation details (number of replications, length, HP filtering) are identical to those in the baseline.

Table 1.8 reports the simulated elasticities of housing market variables with respect to renovation activity under the two protocols, alongside the empirical targets.

Robust patterns across environments. Both environments produce procyclical responses of price, vacancy, and sales to renovation, with elasticities of similar order. The price elasticity (0.38 in RS, 0.41 in DS) lies close to the empirical value of 0.37.

Table 1.8: Cyclical elasticities: data, RS, and DS

	Data	**Random Search**	**Directed Search**
	Elasticity with respect to renovation		
Price, $E_{p,\mathcal{R}}$	0.37	0.38	0.41
Vacancy, $E_{v,\mathcal{R}}$	1.04	0.68	0.36
Sales, $E_{q,\mathcal{R}}$	0.94	0.82	0.73
Time-on-market, $E_{\text{TOM},\mathcal{R}}$	-0.83	-0.99	0.14
submarket R, $E_{\text{TOM}_R,\mathcal{R}}$	—	—	1.12
submarket N, $E_{\text{TOM}_N,\mathcal{R}}$	—	—	-0.36
	Elasticity of price with respect to		
Time-on-market, $E_{p,\text{TOM}}$	-0.10	-0.05	0.38
Vacancy, $E_{p,v}$	0.14	0.55	1.12
Sales, $E_{p,q}$	0.33	0.46	0.56

Note. The Data column reports the empirical moments from Table 1 of the main text. RS and DS are simulated elasticities under the random-search and directed-search protocols respectively. In DS, time-on-market splits across submarkets; the aggregate is the vacancy-weighted average. The price elasticity $E_{p,\text{TOM}}$ in the DS column uses the vacancy-weighted aggregate.

The vacancy and sales elasticities are positive in both models, consistent with the data. This indicates that the central message of the paper—that renovation acts as an adjustment margin shaping prices, sales, and vacancies—does not depend on the search protocol.

Time-on-market: opposing submarket dynamics. The two models give different predictions for the cyclical behavior of time-on-market. The random-search model produces a strongly countercyclical aggregate TOM (-0.99), close to the empirical value (-0.83). In the directed-search model, time-on-market splits into two submarket-specific measures that move in opposite directions over the cycle. As the aggregate state improves, renovation activity rises and the share of renovated listings increases, so buyers reallocate toward the non-renovated submarket where they face less competition. The renovated submarket therefore becomes *less* tight (θ_R falls) while the non-renovated submarket becomes *more* tight (θ_N rises). Time-on-market in the renovated submarket lengthens (procyclical, $E_{\mathrm{TOM}_R,\mathcal{R}} = +1.12$), while time-on-market in the non-renovated submarket shortens (countercyclical, $E_{\mathrm{TOM}_N,\mathcal{R}} = -0.36$). The aggregate TOM is the net of these two opposing forces; in our calibration, the procyclical TOM_R component dominates the vacancy-weighted average, yielding a weakly procyclical aggregate (+0.14). Figure 1.7 illustrates these dynamics.

The mechanism producing this split is the *sorting channel* introduced by directed search: buyers reallocate across submarkets in response to changes in relative tightness. The random-search model has only the *composition channel*, in which buyers meet renovated and non-renovated houses according to their listing shares; this single channel generates a strongly countercyclical aggregate TOM, as in the data. The contrast shows that aggregate time-on-market dynamics depend on the search structure: the random-search environment matches the empirical aggregate TOM elasticity directly, while the directed-search environment decomposes it into opposing submarket components.

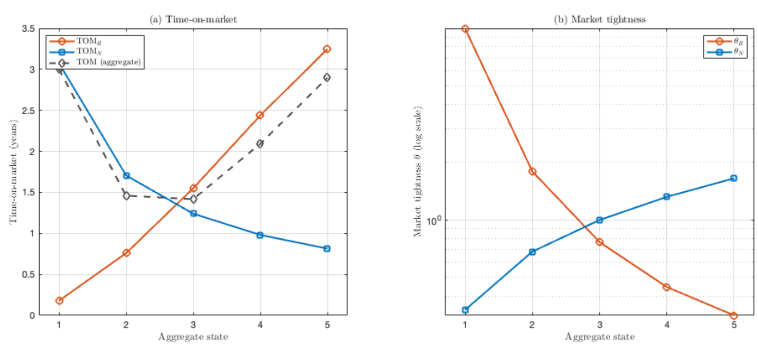


Figure 1.7: Submarket time-on-market and tightness under directed search.
Notes: Panel (a) plots time-on-market in the renovated submarket (TOM_R), the non-renovated submarket (TOM_N), and the aggregate TOM. Panel (b) plots submarket tightness θ_R and θ_N.

Discussion

The directed-search extension delivers two main observations. First, the qualitative picture for prices, vacancies, and sales is robust across the two protocols, with both models producing positive elasticities of comparable magnitude. The renovation channel operates through match surplus in both environments and does not require any specific assumption about the search protocol.

Second, the time-on-market dimension reveals an additional mechanism present only in the directed-search environment. Once buyers can sort across submarkets, the cyclical response of the renovated submarket is sharply different from that of the non-renovated submarket. The aggregate time-on-market observed in the data is consistent with the random-search environment, where a single matching function generates the empirical elasticity directly. The directed-search environment instead splits this dynamic into two opposing submarket components.

These findings address the editor's request to characterize conditions under which renovation amplifies or dampens housing cycles. The search environment itself is one such condition. The qualitative direction of the renovation effect on prices, vacancies, and sales is robust, but the magnitude—and especially the time-on-market response—depends on whether buyers are allowed to direct their search across submarkets.

Chapter 2

Renovation Financing, Credit Frictions, and Housing Market Liquidity

Abstract

This paper studies the role of renovation financing in housing-market dynamics. We build a search-and-matching model in which homeowners obtain external financing through a frictional credit market to upgrade their homes from low- to high-quality, with free entry and Nash bargaining in both the housing and credit markets. Renovation credit frictions affect the housing market through a novel composition channel: changes in the renovation flow shift the composition of vacancies and homeowners between low- and high-quality units. Calibrating the model to the 2012–2019 U.S. housing recovery, we obtain two main findings. First, the renovation credit channel has a negligible effect on the average house price. Second, the channel is an important contributor to the recovery in housing-market liquidity, accounting for about

64% and 71% of the declines in time-to-sell and the vacancy rate, respectively. We thus identify a novel compositional channel through which renovation credit affects housing-market liquidity.

2.1 Introduction

Home renovation is a large and persistent feature of housing markets. In the United States, the home remodeling market has grown steadily over the past decade and reached over \$600 billion in 2024.[1] According to the Home Mortgage Disclosure Act (HMDA), home improvement loan originations rose by 57% during the 2012–2019 U.S. housing recovery, while the average loan size grew by 18%. A growing empirical literature documents the size, drivers, and consequences of renovation activity (e.g., Gyourko & Saiz, 2004; Gyourko & Tracy, 2006; Mamre & Sommervoll, 2024), yet the standard search-and-matching framework for the housing market abstracts from renovation, treating the housing stock as homogeneous in quality and static in composition. Recent extensions introduce credit frictions on the buyer side through mortgage credit (Gabrovski & Ortego-Marti, 2021b) and on the developer side through construction credit (Gabrovski & Ortego-Marti, 2025). The homeowner's renovation margin, a distinct channel through which credit frictions shape the housing market, remains unexplored.

This chapter takes up this question, studying the effect of renovation credit frictions on the housing market during the 2012–2019 recovery, with a focus on house prices, housing-market liquidity, and the volume of renovation lending. We build a search-and-matching model in which homeowners finance renovations through a frictional credit market, and the resulting flow of upgrades shapes the composition of the

[1] Source: Joint Center for Housing Studies of Harvard University, *Improving America's Housing 2025*.

housing stock between low- and high-type units. The framework features two frictional markets, a housing market in the spirit of Pissarides (2000) and a credit market in the spirit of Wasmer and Weil (2004), linked through the homeowner's renovation decision. Houses come in two quality types, and renovation upgrades a low-quality home into a high-quality one, a stylized representation of the within-market quality heterogeneity documented by Landvoigt, Piazzesi, and Schneider (2015).

The framework is closest to Gabrovski and Ortego-Marti (2025) and Gabrovski and Ortego-Marti (2021b), but differs from both in how the credit channel transmits to housing-market outcomes. In their settings, credit frictions act on the inflow of new construction or on the entry of mortgage-financed buyers. In ours, credit frictions instead govern the rate at which low-type homes are upgraded into high-type ones. Because high-type homes deliver higher utility to their occupants and command a higher sale price, a larger flow of renovations raises the value of being a high-type homeowner. This higher value propagates to both sides of the housing market. It raises the surplus that buyers expect from a match with a high-type vacancy, inducing additional buyer entry, and it raises the value of becoming an applicant in the credit market, inducing additional applicant entry. The resulting rise in buyer entry tightens the housing market and accelerates the recovery in time-to-sell and the vacancy rate.

We calibrate the model to the 2012–2019 U.S. housing recovery, identifying five structural shocks. These shocks govern housing demand, construction costs, credit-market matching efficiency, and the bargaining powers of housing sellers and financiers. They jointly match a set of stylized facts about the period. The housing-market facts are an increase of 39.61% in the average house price, a decline of 25.96% in time-to-sell, and a decline of 30.80% in the homeowner vacancy rate.[2] On the

[2]These magnitudes are broadly consistent with those reported in Gabrovski and Ortego-Marti (2025) for the same period. The minor discrepancies reflect our use of annual rather than quarterly data, chosen to match the annual frequency of the HMDA renovation lending series.

renovation side, we document two new patterns. Renovation loan originations rose by 57.41% and the average loan size rose by 18.48%.

A counterfactual decomposition reveals two main findings on the renovation credit channel. First, the credit channel has a negligible effect on the average house price. In the absence of the credit shocks, the average price would still have risen by 39.13% rather than the observed 39.61%, so the credit channel accounts for only 1.2% of the price recovery. Renovation credit does not change how many homes are built or how many buyers can finance a purchase. It only changes the composition of homes for sale, and this compositional shift is too small to move the average house price appreciably.

Second, the renovation credit channel is an important contributor to the recovery in housing-market liquidity. The channel accounts for about 64% of the observed decline in time-to-sell and 71% of the observed decline in the vacancy rate. Absent the credit shocks, time-to-sell and the vacancy rate would have fallen by substantially less than they did in the data. The renovation flow raises the value of being a high-type homeowner, which in turn raises both buyer entry and applicant entry into their respective markets. The rise in buyer entry tightens the housing market and accelerates the recovery in time-to-sell and the vacancy rate. We identify this as a novel compositional channel of liquidity.

Related literature. This chapter contributes to several literatures. The first is the search-and-matching literature on housing markets, dating to Wheaton (1990) and developed in a large body of work using matching functions à la Diamond-Mortensen-Pissarides (Burnside et al., 2016; Diaz & Jerez, 2013; Gabrovski & Ortego-Marti, 2019; Genesove & Han, 2012; Head et al., 2014; Ngai & Sheedy, 2024; Novy-Marx, 2009; Piazzesi & Schneider, 2009); Han and Strange (2015) provides an extensive review.

Existing work in this literature treats the housing stock as homogeneous in quality. We introduce a low–high quality distinction and an explicit renovation margin, motivated by empirical evidence on substantial within-market quality heterogeneity (Landvoigt et al., 2015), and show that this distinction generates a new channel through which credit markets affect housing-market dynamics.

The second is the credit-search literature in housing, which builds on the general credit-search methodology of Petrosky-Nadeau and Wasmer (2017); Wasmer and Weil (2004). Gabrovski and Ortego-Marti (2021b) and Gabrovski and Ortego-Marti (2025) introduce credit-search frictions on the buyer and developer sides of the housing market, respectively. We extend this literature to the homeowner side by introducing renovation credit frictions. The resulting channel contributes substantially to housing-market liquidity while having a negligible effect on house prices, in contrast to the price effects emphasized in the buyer-credit and developer-credit literatures. More broadly, our chapter relates to search-theoretic models of housing with financially constrained households (Garriga & Hedlund, 2020; Guren & McQuade, 2020; Head, Sun, & Zhou, 2023; Hedlund, 2016). These papers focus on mortgage contracts and foreclosure dynamics as the primary credit channel, whereas we study the distinct margin of renovation financing.

The third is the empirical literature on home renovation (Choi, Hong, Kubik, & Thompson, 2014; Gyourko & Saiz, 2004; Gyourko & Tracy, 2006; Mamre & Sommervoll, 2024), which documents the size, drivers, and heterogeneity of renovation activity. We contribute new stylized facts on the volume and size of renovation lending during the 2012–2019 U.S. housing recovery, and integrate the renovation margin into a search-theoretic model of housing-market dynamics.

The remainder of the chapter is organized as follows. Section 2.2 presents the model. Section 2.3 presents the quantitative analysis, including a counterfactual decomposition of the renovation credit channel. Section 2.4 concludes.

2.2 Model

Time is continuous. Agents are infinitely lived, risk-neutral, and discount the future at rate r. The economy is populated by households, financiers, and real estate agents. Households are either buyers, who search for a home to purchase, or homeowners, who own a home of either low (L) or high (H) quality; low-type homeowners who have decided to renovate and are searching for a financier are referred to as applicants. Financiers supply renovation loans through the credit market. Real estate agents intermediate transactions between buyers and sellers in the housing market.[3] High-type homes are produced through renovation, which converts a low-type home into a high-type home and requires external financing obtained in the credit market.

The economy features two frictional markets, both subject to search and matching frictions and free entry on both sides. In the housing market, it takes time and resources for buyers to find a suitable home and for sellers to find a buyer; buyers incur a search cost and sellers incur a user cost while waiting to be matched. In the credit market, it takes time and resources for applicants to find a financier willing to fund a renovation, and for financiers to find a borrower; both sides incur participation costs while searching. Within each market, prices and repayments are determined by Nash bargaining, and matching rates are determined endogenously through entry conditions.

[3] The role of real estate agents in the model is to capture the convex search cost incurred by buyers. The model's predictions are unchanged if buyers search directly without the help of a realtor.

The model integrates two ingredients that have been studied separately in the housing search literature. First, a low–high quality distinction in housing, which allows renovation to be treated as an explicit margin of housing-market adjustment. A low-type home can be upgraded into a high-type home that delivers higher utility to its owner. Second, a credit market in which homeowner-borrowers must search for financiers in order to undertake a renovation, following the search-theoretic approach of Wasmer and Weil (2004) and Gabrovski and Ortego-Marti (2021b). Together, these elements yield a framework in which renovation credit shapes housing-market dynamics through the quality composition of the housing stock.

2.2.1 Environment

There is a unit measure of homeowners, each occupying either a low-type home or a high-type home. Buyers and sellers participate in the housing market subject to free entry. Sellers list either a low-type vacancy or a high-type vacancy. Applicants are low-type homeowners who have decided to finance a renovation; they search for a financier in the credit market. Financiers are intermediaries who supply renovation loans subject to free entry. Houses depreciate at rate δ. A low-type homeowner receives a renovation opportunity at Poisson rate λ, capturing the stochastic arrival of life events that motivate a renovation. Both low- and high-type homeowners face a separation shock at rate s, in which case the home is listed for sale. High-type homes additionally face a downgrade shock at rate δ_d, returning them to the low-type state; this captures the gradual decay of renovation quality, so that a renovated home does not retain its high-type status indefinitely.[4]

[4] We use the terms vacancies and homes listed for sale interchangeably.

Housing market. Buyers and sellers meet through a matching technology. Let b denote the measure of buyers and $v = v_L + v_H$ the measure of vacancies, with composition shares

$$\pi_L \equiv \frac{v_L}{v}, \qquad \pi_H \equiv \frac{v_H}{v} = 1 - \pi_L. \tag{2.1}$$

The composition shares π_L and π_H play a central role in the mechanism of the model. They govern the probability that a buyer's random encounter is with a low-type or a high-type vacancy, and they respond endogenously to changes in renovation activity. Housing-market tightness is $\theta \equiv b/v$. We assume a Cobb-Douglas matching function $M_H(b, v) = \mu_H \, b^{\alpha_m} \, v^{1-\alpha_m}$, so that buyers find a vacancy at rate $m(\theta) \equiv M_H(1, \theta^{-1})$, and a vacancy meets a buyer at rate $\theta \, m(\theta)$. Buyers can be matched with both L and H vacancies. Once a match is formed, the buyer and the seller engage in Nash bargaining over the sale price; the transaction is completed and the match dissolves. Equilibrium prices for the two qualities, p_L and p_H, emerge from this bargaining protocol.

Following Gabrovski and Ortego-Marti (2019), buyers require the services of a representative realtor to search for vacancies. Searching is a costly action for the realtor, so she charges a flow fee $c^B(b)$ in exchange for her services. Assuming that the realtor's cost of servicing b buyers is $\bar{c} \, b^{\gamma+1}/(\gamma + 1)$, and that the realtor's revenue from servicing b buyers equals $b \, c^B(b)$, profit maximization implies $c^B(b) = \bar{c} \, b^{\gamma}$. The exponent γ governs the strength of the congestion effect. As the number of buyers b rises, the per-buyer cost of being matched with vacancies rises through the realtor's congestion technology. Sellers incur a flow search cost c^S until a buyer is found.

Credit market. Applicants and financiers meet through a credit-market matching technology analogous to that of the housing market. Let $\mathcal{A}$ denote the measure of applicants and $\mathcal{F}$ the measure of financiers. Credit-market tightness is $\phi \equiv \mathcal{A}/\mathcal{F}$.

We assume a Cobb-Douglas matching function $M_C(\mathcal{A}, \mathcal{F}) = \mu_f \, \mathcal{A}^{\alpha_f} \, \mathcal{F}^{1-\alpha_f}$, so that an applicant matches with a financier at rate $f(\phi) \equiv M_C(1, \phi^{-1})$, and a financier matches with an applicant at rate $\phi f(\phi)$. The parameter μ_f governs the efficiency of the credit-market matching technology and plays a central role in the model's transmission of credit shocks to housing-market outcomes. Applicants incur a flow search cost c^A while searching; financiers incur a flow cost c^F until they form a match. Once a match is formed, the applicant and the financier engage in Nash bargaining over the lump-sum repayment ρ. The financier then funds the renovation cost k^R, the borrower commits to repaying ρ, and the home transitions to the high-type state.[5]

Two features of the environment shape the transmission of credit frictions. First, renovation converts low-type homes into high-type homes without adding new units to the housing stock; it operates on the quality of existing homes rather than on their quantity. Second, renovations are financed entirely through the credit market, so credit-market conditions translate directly into renovation activity. We further assume that buyers face no financing constraint when purchasing a home, of either quality type; this choice deliberately abstracts from the mortgage- financing margin studied in Gabrovski and Ortego-Marti (2021b); Garriga and Hedlund (2020) so as to isolate the renovation credit channel. The credit channel therefore operates on the quality composition of the housing stock, rather than on its quantity or on buyer purchasing power.

[5]Applicants do not face separation shocks while searching. Once a homeowner has decided to renovate, the home cannot be put up for sale during the search phase. This assumption simplifies the law of motion for applicants. Allowing for separation during search adds an outflow $s\,\mathcal{A}$ to the applicant law of motion but does not change the qualitative features of the model.

2.2.2 Bellman Equations

Let H_L and H_H denote the value functions of low-type and high-type homeowners, and V_L and V_H the value functions of sellers listing low- and high-type vacancies. The Bellman equation for the low-type homeowner is

$$(r+\delta)\, H_L = x + s\,(V_L - H_L) + \lambda\,(A - H_L). \tag{2.2}$$

A low-type homeowner enjoys flow utility x from housing services. At rate s a separation shock arrives, after which the home is listed for sale and the homeowner becomes a seller with value V_L. At rate λ a renovation opportunity arrives, after which the homeowner enters the credit market as an applicant with value A. The effective discount rate $r+\delta$ reflects both time discounting and the possibility that the home is destroyed through depreciation.

A high-type homeowner enjoys flow utility $x\mu$, where $\mu > 1$ is the quality multiplier of renovated homes. The multiplier μ captures the additional utility flow generated by the renovation, which is what makes renovation valuable to the homeowner and renders the loan repayment ρ acceptable in bargaining. At rate s a separation shock arrives and the home is listed for sale as a high-type vacancy, leaving the homeowner with value V_H. At rate δ_d a downgrade shock arrives and the home reverts to the low-type state, leaving the homeowner with value H_L. The Bellman equation for the high-type homeowner is

$$(r+\delta)\, H_H = x\mu + s\,(V_H - H_H) + \delta_d\,(H_L - H_H). \tag{2.3}$$

A low-type homeowner who has entered the credit market is an applicant. While searching for a financier, the applicant incurs flow search cost c^A.[6] At rate $f(\phi)$ the applicant matches with a financier and the renovation project is executed. The financier funds the renovation cost k^R, the applicant commits to a flow repayment ρ until the home is destroyed, and the homeowner becomes a high-type owner with value H_H. Given risk-neutrality and the effective discount rate $r + \delta$, the flow repayment ρ has present value $\rho/(r + \delta)$ at the time of match.[7] The Bellman equation for the applicant is

$$(r + \delta)\, A = -c^A + f(\phi) \left(H_H - \frac{\rho}{r + \delta} - A \right). \tag{2.4}$$

Note that the renovation cost k^R does not appear in the borrower's value function, since it is fully funded by the financier; the borrower's obligation is captured by the present value of repayments $\rho/(r + \delta)$.

Sellers of both types incur flow search cost c^S. At rate $\theta m(\theta)$ a seller meets a buyer and the home is sold at price p_L or p_H determined by Nash bargaining. The Bellman equations for the two types of sellers are

$$(r + \delta)\, V_L = -c^S + \theta m(\theta)\, (p_L - V_L), \tag{2.5}$$

$$(r + \delta)\, V_H = -c^S + \theta m(\theta)\, (p_H - V_H). \tag{2.6}$$

[6] The applicant does not receive flow utility x during the search phase; including it would shift the level of A without changing the model's mechanism.

[7] This formulation is equivalent to one in which the applicant transfers the lump-sum $\rho/(r + \delta)$ to the financier at the time of match. It is also equivalent to a formulation in which the homeowner pays the flow ρ as part of the high-type Bellman equation (2.3), with H_H correspondingly redefined as the value of being high-type net of repayment obligations. We adopt the flow-repayment formulation with ρ appearing only in the applicant and financier value functions because it simplifies the exposition and the solution, following Gabrovski and Ortego-Marti (2021b).

Sellers of the two types face the same search cost and the same meeting rate; what differs is the price they receive, which is determined by bargaining over different match surpluses.

A buyer incurs flow search cost $c^B(b)$. At rate $m(\theta)$ the buyer meets a vacancy. With probability π_L the vacancy is low-type and the match yields net surplus $H_L - p_L - B$; with probability π_H the vacancy is high-type and the match yields net surplus $H_H - p_H - B$. The Bellman equation for the buyer is

$$r\,B = -c^B(b) + m(\theta)\Big[\pi_L\,(H_L - p_L - B) + \pi_H\,(H_H - p_H - B)\Big]. \tag{2.7}$$

The composition shares π_L and π_H provide the channel through which renovation activity, by shifting the quality mix of vacancies, affects buyer entry and ultimately equilibrium tightness.[8]

A financier incurs flow cost c^F. At rate $\phi f(\phi)$ the financier matches with an applicant. The financier funds the renovation cost k^R and receives a flow repayment ρ with present value $\rho/(r+\delta)$. The Bellman equation for the financier is

$$r\,F = -c^F + \phi f(\phi)\,\left(\frac{\rho}{r+\delta} - k^R - F\right). \tag{2.8}$$

At match, the financier's gross profit is the present value of bargained repayments net of the renovation cost funded, $\rho/(r+\delta) - k^R$.

[8] Recall that buyers face no financing constraint, as discussed in Section 2.2.1. The composition mechanism studied here operates through the supply side of vacancies, via the rate at which low-type homes are upgraded, which then transmits to buyer entry through the composition shares π_L and π_H.

2.2.3 Nash Bargaining

In both the housing and credit markets, the surplus from matching is split according to Nash bargaining (Nash et al., 1950; Rubinstein, 1982). Following Gabrovski and Ortego-Marti (2021b) and Petrosky-Nadeau and Wasmer (2017), we assume that bargaining is sequential. The applicant and the financier take housing prices as given, while the buyer and the seller anticipate the credit-market contract.

In the housing market, for a match of type $i \in \{L, H\}$, let $S^{Bi} \equiv H_i - p_i - B$ denote the buyer's surplus and $S^{Si} \equiv p_i - V_i$ denote the seller's surplus. The price p_i solves the Nash bargaining problem

$$p_i = \arg\max_{p_i} (S^{Si})^{\beta} (S^{Bi})^{1-\beta}, \quad i \in \{L, H\}, \tag{2.9}$$

where β is the seller's bargaining strength. The first-order condition yields the sharing rule

$$\beta\, S^{Bi} = (1-\beta)\, S^{Si}, \quad i \in \{L, H\}. \tag{2.10}$$

Letting $S^i \equiv S^{Bi} + S^{Si} = H_i - B - V_i$ denote the total match surplus for a sale of type i, the sharing rule implies $S^{Si} = \beta S^i$ and $S^{Bi} = (1-\beta) S^i$. Solving for the bargained prices yields

$$p_L = \beta\,(H_L - B) + (1-\beta)\, V_L, \tag{2.11}$$

$$p_H = \beta\,(H_H - B) + (1-\beta)\, V_H. \tag{2.12}$$

The bargained price is a weighted average of the buyer's net valuation $H_i - B$ and the seller's outside option V_i, with weights given by the bargaining powers.

In the credit market, let $S^A \equiv H_H - \rho/(r+\delta) - A$ denote the applicant's surplus and $S^F \equiv \rho/(r+\delta) - k^R - F$ denote the financier's surplus when they form a match. The repayment ρ solves the Nash bargaining problem

$$\rho = \arg\max_{\rho} (S^A)^{1-\eta}(S^F)^{\eta}, \tag{2.13}$$

where η is the financier's bargaining strength. The first-order condition yields the sharing rule

$$\eta\, S^A = (1-\eta)\, S^F. \tag{2.14}$$

Letting $S_0 \equiv S^A + S^F = H_H - A - k^R - F$ denote the total match surplus in the credit market, the sharing rule implies $S^A = (1-\eta)S_0$ and $S^F = \eta S_0$. Solving for the repayment yields

$$\frac{\rho}{r+\delta} = (1-\eta)(H_H - A) + \eta\,(k^R + F). \tag{2.15}$$

As in the housing market, the bargained repayment is a weighted average of the applicant's net valuation $H_H - A$ and the financier's cost $k^R + F$, with weights given by the bargaining powers.

2.2.4 Equilibrium

The equilibrium of the model is characterized by three sets of conditions. The first set comprises the free-entry conditions in the housing and credit markets. Buyers, financiers, and housing all enter their respective markets up to the point where the expected gains from participation just cover their costs. The second set requires that the Bellman equations and bargaining outcomes are internally consistent. Prices and repayments reflect the surpluses each pair of agents anticipates from a match, given the equilibrium tightness in each market. The third set requires that the laws of motion produce stationary stocks of homeowners, applicants, and vacancies. We characterize each in turn, beginning with the free-entry conditions.

Free entry of buyers drives the value of being a buyer to zero. Substituting $B = 0$ into the buyer Bellman equation (2.7) and using the prices (2.11)–(2.12) gives the buyer-entry (BE) condition,

$$\text{BE:} \quad \frac{c^B(b)}{m(\theta)} = (1-\beta)\Big[\pi_L\,(H_L - V_L) + \pi_H\,(H_H - V_H)\Big]. \tag{2.16}$$

The condition equates the buyer's expected search cost (left-hand side) to the buyer's share of the expected match surplus (right-hand side). The left-hand side combines the flow search cost $c^B(b)$ with the expected duration of search $1/m(\theta)$. The right-hand side is the buyer's bargaining share $(1-\beta)$ applied to the expected match surplus, where the expectation is taken over the two vacancy types the buyer might meet, with weights given by the composition shares π_L and π_H. The BE condition therefore links the equilibrium measure of buyers to the housing-market tightness and the composition of vacancies. As π_H rises, for example when the credit channel expands the flow of high-type vacancies, the average match surplus for a buyer rises as well, raising buyer entry and equilibrium tightness. This is the composition channel through which credit-market shocks transmit to the housing market.

Free entry of new homes drives the low-type seller value to the construction cost, $V_L = k$. Substituting $V_L = k$ into the seller Bellman equation (2.5) gives the housing-entry (HE) condition,

$$\text{HE:} \quad \frac{c^S + (r+\delta)\,k}{\theta m(\theta)} = p_L - k. \tag{2.17}$$

The left-hand side is the expected total cost of producing and selling a home, decomposed into the seller's flow search cost c^S and the user cost of capital $(r+\delta)\,k$, divided by the meeting rate $\theta m(\theta)$ at which the seller expects to encounter a buyer. The right-hand side is the seller's profit margin per sale, $p_L - k$. The HE condition implicitly determines the equilibrium housing-market tightness θ and the low-type price p_L. A fall in $\theta m(\theta)$ tightens the condition, requiring a higher p_L to restore equality.

Similarly, free entry of financiers drives the value of being a financier to zero. Substituting $F = 0$ into the financier Bellman equation (2.8) gives the credit-entry (CE) condition,

$$\text{CE:} \quad \frac{c^F}{\phi f(\phi)} = \frac{\rho}{r+\delta} - k^R. \tag{2.18}$$

The condition equates the financier's expected search cost (left-hand side) to the financier's net profit (right-hand side). The left-hand side combines the flow search cost c^F with the expected duration of search $1/(\phi f(\phi))$. The right-hand side, $\rho/(r+\delta) - k^R$, is the present value of the bargained repayments minus the renovation cost the financier funds at match. The CE condition therefore plays the same role for financiers as the HE condition plays for housing sellers. It links the matching rate in the credit market to the net profit per match.

Combining the Nash-bargained repayment with the financier's free-entry condition allows us to rewrite both in terms of match surpluses alone. Setting $F = 0$ in (2.15) gives

$$\frac{\rho}{r+\delta} = (1-\eta)\,(H_H - A) + \eta\, k^R, \tag{2.19}$$

which expresses the present value of the repayment in terms of the homeowner's renovation surplus $H_H - A$ and the renovation cost k^R. Substituting (2.19) into the CE condition (2.18) yields the financier's free-entry condition in surplus form,

$$\text{CE}': \quad \frac{c^F}{\phi f(\phi)} = (1-\eta)\left(H_H - A - k^R\right). \tag{2.20}$$

The condition states that the financier's expected search cost per match equals their share $(1-\eta)$ of the total match surplus $H_H - A - k^R$, where $H_H - A$ is the homeowner's gain from being renovated and k^R is the renovation cost advanced by the financier.

Substituting (2.19) into the applicant Bellman equation (2.4) similarly yields the applicant's Bellman equation in surplus form,

$$(r + \delta)\, A = -c^A + f(\phi)\, \eta \left(H_H - A - k^R\right), \tag{2.21}$$

which makes explicit that the applicant earns a share η of the total match surplus upon matching with a financier.

Combining (2.20) and (2.21), the credit-market tightness ϕ satisfies[9]

$$\frac{c^F}{\phi f(\phi)} = (1 - \eta)\, \frac{(H_H - k^R)(r + \delta) + c^A}{r + \delta + f(\phi)\, \eta}, \tag{2.22}$$

which determines ϕ jointly with the high-type homeowner value H_H. The credit channel thus couples the credit-market block to the housing-market block through H_H. An improvement in the credit market, for example a fall in c^F or in matching frictions, raises ϕ, raises H_H through the applicant's expected gain, and feeds back into the housing market through the composition channel.

[9]Unlike in the standard Wasmer–Weil environment, the credit-market tightness ϕ here cannot be expressed in closed form as a function of relative search costs and bargaining weights alone. The reason is that applicants are not free entrants. They arrive only when a low-type homeowner receives a renovation opportunity at the Poisson rate λ, so A is determined by its own Bellman equation rather than driven to zero by entry.

We now derive closed-form expressions for the equilibrium value functions. The high-type seller value V_H follows from (2.6), using the bargained price $p_H = \beta H_H + (1-\beta)V_H$ from (2.12) and solving for V_H,

$$V_H = \frac{-c^S + \theta m(\theta)\,\beta\,H_H}{r + \delta + \theta m(\theta)\,\beta}. \tag{2.23}$$

The high-type seller value is a discounted weighted average of the flow search cost paid during search and the share β of the homeowner value received upon sale.

The high-type homeowner value H_H in turn satisfies, from (2.3),

$$H_H = \frac{x\mu + s\,V_H + \delta_d\,H_L}{r + \delta + s + \delta_d}, \tag{2.24}$$

which expresses H_H as a discounted weighted average of three flow terms: the renovated-flow utility $x\mu$, the seller value, and the low-type value. Substituting (2.23) into (2.24) and solving for H_H gives the closed-form expression for the high-type homeowner value,

$$H_H = \frac{x\mu + \delta_d\,H_L - \dfrac{s\,c^S}{r + \delta + \theta m(\theta)\,\beta}}{(r + \delta + s + \delta_d) - \dfrac{s\,\theta m(\theta)\,\beta}{r + \delta + \theta m(\theta)\,\beta}}. \tag{2.25}$$

The dependence on housing-market tightness $\theta m(\theta)$ captures a feedback from housing-market liquidity. Faster sales shorten the expected duration of the seller phase, raising H_H.

With $V_L = k$, the low-type homeowner value follows from (2.2),

$$H_L = \frac{x + s\,k + \lambda\,A}{r + \delta + s + \lambda}. \tag{2.26}$$

The low-type value is a discounted weighted average of the flow utility x, the construction cost k, and the applicant value A. Solving (2.21) for the applicant value gives

$$A = \frac{-c^A + f(\phi)\,\eta\,(H_H - k^R)}{r + \delta + f(\phi)\,\eta}. \tag{2.27}$$

Equation (2.27) captures the value of being in the credit-market search pool. The applicant incurs a flow cost c^A while searching and receives the share η of the match surplus $H_H - A - k^R$ upon matching with a financier. Because A depends on H_H and H_L depends on A, the housing-market and credit-market blocks are coupled through the homeowner values.

The applicant value (2.27) can be substituted into (2.26) to express the low-type homeowner value in terms of H_H and the credit-market tightness,

$$H_L = \frac{(x + s\,k)\,(r + \delta + f(\phi)\,\eta) + \lambda\,f(\phi)\,\eta\,(H_H - k^R) - \lambda\,c^A}{(r + \delta + s + \lambda)\,(r + \delta + f(\phi)\,\eta)}. \tag{2.28}$$

This expression shows how the credit market enters the low-type homeowner value. The option to renovate, exercised at rate λ, yields the applicant's share η of the renovation surplus $H_H - k^R$, net of the expected applicant search cost c^A.

Similarly, the high-type seller value (2.23) can be substituted into (2.24) to give the high-type homeowner value as a function of H_L and the housing-market tightness,

$$H_H = \frac{(r + \delta + \theta m(\theta)\,\beta)\,(x\mu + \delta_d\,H_L) - s\,c^S}{(r + \delta + s + \delta_d)\,(r + \delta + \theta m(\theta)\,\beta) - s\,\theta m(\theta)\,\beta}. \tag{2.29}$$

Equations (2.28) and (2.29) can be solved by mutual substitution to yield H_L and H_H as functions of the tightnesses (θ, ϕ) alone.

Finally, applying the free-entry conditions, the bargained prices (2.11)–(2.12) reduce to

$$\text{PPL:}\quad p_L = \beta\, H_L + (1-\beta)\, k, \tag{2.30}$$

$$\text{PPH:}\quad p_H = \frac{\beta\,(r+\delta+\theta m(\theta))\, H_H - (1-\beta)\, c^S}{r+\delta+\theta m(\theta)\,\beta}, \tag{2.31}$$

where the second expression follows from substituting the closed-form V_H in (2.23). The low-type price is a weighted average of the low-type homeowner value and the construction cost, with weight β on the seller's side. Equation (2.31) shows that the high-type price loads positively on H_H and negatively on the seller's flow search cost c^S. The dependence on $\theta m(\theta)$ captures a feedback from housing-market liquidity to high-type prices. Faster sales reduce the expected duration of the seller phase, raising the seller's outside option V_H and therefore the bargained price p_H for a given H_H.

We now turn to the laws of motion that pin down the stocks of agents in steady state. Let h_L, h_H denote the measures of low- and high-type homeowners, $\mathcal{A}$ the measure of applicants, and v_L, v_H the measures of low- and high-type vacancies. Let n denote the flow of new low-type vacancies created through free entry of construction. The laws of motion for vacancies are

$$\dot{v}_L = n + s\, h_L - \theta m(\theta)\, v_L - \delta\, v_L, \tag{2.32}$$

$$\dot{v}_H = s\, h_H - \theta m(\theta)\, v_H - \delta\, v_H. \tag{2.33}$$

Equation (2.32) describes the low-type vacancy stock, which is supplied by two inflows: the construction flow n from free entry of developers, and the flow of separations $s\, h_L$ from existing low-type homeowners.[10] Equation (2.33) describes the high-type

[10]We do not track newly constructed and existing low-type vacancies separately because they are identical in price, seller value, and matching rate; only the source of inflow differs.

vacancy stock, supplied only through separations of high-type homeowners at rate $s\,h_H$. Both stocks are depleted by sales at rate $\theta m(\theta)$ and by depreciation at rate δ.

The laws of motion for homeowners are

$$\dot{h}_L = m(\theta)\,\pi_L\,b + \delta_d\,h_H - \Big(s + \lambda + \delta\Big)\,h_L, \tag{2.34}$$

$$\dot{h}_H = m(\theta)\,\pi_H\,b + f(\phi)\,\mathcal{A} - \Big(s + \delta_d + \delta\Big)\,h_H. \tag{2.35}$$

The stock of low-type homeowners grows from new home purchases and from downgrades of high-type homes, and shrinks through separations, entry into the renovation pipeline, and depreciation. The stock of high-type homeowners grows from purchases of high-type vacancies and from renovations completed in the credit market, and shrinks through separations, downgrades, and depreciation. The completed renovation flow $f(\phi)\,\mathcal{A}$ is the central object linking the credit market to the housing market. It determines the steady-state share of high-type homeowners and, through separations, the share of high-type vacancies.

The law of motion for applicants is

$$\dot{\mathcal{A}} = \lambda\,h_L - f(\phi)\,\mathcal{A} - \delta\,\mathcal{A}, \tag{2.36}$$

with inflow $\lambda\,h_L$ from low-type homeowners receiving renovation opportunities, and outflows from successful credit matches at rate $f(\phi)$ and from depreciation at rate δ. The composition shares satisfy

$$\pi_L = \frac{v_L}{v_L + v_H}, \qquad \pi_H = 1 - \pi_L. \tag{2.37}$$

We focus on the steady-state equilibrium, in which all stocks are constant $\dot{v}_L = \dot{v}_H = \dot{h}_L = \dot{h}_H = \dot{\mathcal{A}} = 0$. Combining the Bellman equations, the bargaining outcomes, the free-entry conditions, and the steady-state laws of motion gives the formal definition of equilibrium.

Definition 2.1. *A steady-state equilibrium of the baseline model consists of a tuple* $\{\theta, \phi, \pi_L, b, p_L, p_H, \rho, V_H, H_L, H_H, h_L, h_H, \mathcal{A}, v_L, v_H, n\}$ *that satisfies: (i) the Bellman equations* (2.2)–(2.8)*; (ii) the BE condition* (2.16)*; (iii) the HE condition* (2.17)*; (iv) the CE condition* (2.18)*; (v) the tightness condition* (2.22)*; (vi) the PPL condition* (2.30)*; (vii) the PPH condition* (2.31)*; (viii) the repayment condition* (2.19)*; (ix) the steady-state laws of motion* (2.32)–(2.36)*; (x) the consistency conditions* $\theta = b/v$ *and* $\phi = \mathcal{A}/\mathcal{F}$*.*

The equilibrium of the present model is fully simultaneous. Because applicants are not free entrants, the credit-market tightness ϕ and the high-type homeowner value H_H are determined jointly with the housing-market tightness θ, the low-type price p_L, and the low-type value H_L. Operationally, the equilibrium is computed as the solution to the simultaneous system formed by the HE condition (2.17), the tightness condition (2.22), the closed-form expressions (2.29), (2.28), and (2.27), together with the bargained prices (2.30)–(2.31). This is a nonlinear system of six equations in six unknowns $\{\theta, \phi, p_L, H_L, H_H, A\}$, with the remaining equilibrium objects following from the closed-form expressions and laws of motion. We verify numerically that a solution exists and is unique for the parameter values used in Section 2.3.

The model embeds a credit channel that links credit-market frictions to housing-market outcomes through two interacting mechanisms. On the credit side, a reduction in the financier's flow search cost c^F raises the credit-market tightness ϕ through (2.22), while an increase in the matching efficiency μ_f raises the matching rates $f(\phi)$ and $\phi f(\phi)$ directly. Because applicants are not free entrants, both shocks also feed back into ϕ indirectly through the high-type homeowner value H_H. An improvement in credit-market conditions raises the applicant's expected gain from search, raises H_H, and further adjusts ϕ through (2.22).

The credit-market adjustment reaches the housing market through a composition effect specific to the renovation environment of this chapter. A higher renovation flow $f(\phi)\,\mathcal{A}$ raises the steady-state stock of high-type homeowners, which translates through separations into a larger flow of high-type vacancies and a higher π_H. The average vacancy that a buyer encounters is then more likely to be high-type, raising the buyer's expected match surplus and the bargained prices, with buyer entry adjusting through the BE condition (2.16) and equilibrium tightness θ determined jointly through the HE condition (2.17). This composition channel distinguishes the renovation credit channel of this chapter from the developer credit channel of Gabrovski and Ortego-Marti (2025), which operates on new-construction inflow, and from the mortgage credit channel of Gabrovski and Ortego-Marti (2021b), which operates on buyer entry directly.

2.3 Quantitative Analysis

This section quantifies the contribution of the renovation credit channel to the 2012–2019 U.S. housing recovery. Section 3.1 documents a set of stylized facts on housing-market outcomes and renovation lending that target the calibration. Section 3.2 describes the calibration strategy, distinguishing parameters set externally from those identified internally through the 2012 steady state and the 2012–2019 transition. Section 3.3 reports the calibrated equilibrium and the recovered structural shocks. Section 3.4 isolates the credit channel through a counterfactual decomposition that holds the credit-side shocks at their 2012 values while leaving the housing-side shocks at their 2019 values.

2.3.1 Stylized Facts

We document a set of stylized facts characterizing the U.S. housing market recovery between 2012 and 2019, with particular focus on home renovation activity and renovation lending. Panel A of Table 2.1 summarizes the recovery of housing prices, liquidity, and inventory using standard housing-market sources. The average house price is the seasonally adjusted Case-Shiller U.S. National Home Price Index, deflated by the Consumer Price Index for All Urban Consumers: All Items Less Shelter, CPI-LS. Time-to-sell is the median number of months on the sales market for newly completed homes from the New Residential Sales release of the U.S. Census Bureau and the U.S. Department of Housing and Urban Development, following the measurement convention of Gabrovski and Ortego-Marti (2021b, 2025). The vacancy rate is the homeowner vacancy rate from the Housing Vacancies and Homeownership release of the U.S. Census Bureau. Panel B of Table 2.1 introduces new facts on renovation lending, constructed from the Home Mortgage Disclosure Act (HMDA) National Aggregate Report.[11] We include conventional, government-insured (FHA), and government-guaranteed (FSA, RHS, and VA) loans with renovation as the stated loan purpose, and deflate the average loan size by the CPI-LS. We work at the annual frequency throughout, consistent with the availability of the HMDA data and with the relevant horizons of renovation projects and renovation credit. For each series, we regress the values on a constant and a linear time trend over 2012–2019, and report the percentage change between the fitted 2012 and 2019 values. Figure 2.1 plots the raw series and the fitted linear trends for all five moments.

[11] HMDA data through 2017 were collected and disclosed by the member agencies of the Federal Financial Institutions Examination Council (FFIEC); from 2018 onward, HMDA data are collected and published by the Consumer Financial Protection Bureau (CFPB) on behalf of FFIEC under the 2015 HMDA Final Rule. The reporting requirements and data fields changed in 2018, but the home-improvement loan-purpose classification used in our analysis is consistent across the pre- and post-2018 periods.

Table 2.1: Stylized Facts of the 2012–2019 Housing Recovery

Series	Percentage Change
Panel A. Housing Market Variables	
Average House Price	+39.61%
Time-to-Sell	−25.96%
Vacancy Rate	−30.80%
Panel B. Renovation and Credit Variables	
Renovation Loan Originations	+57.41%
Average Renovation Loan Size	+18.48%

Notes: All series are at the annual frequency. Panel A reports stylized facts on housing-market variables. The average house price is the seasonally adjusted Case-Shiller U.S. National Home Price Index (S&P Dow Jones Indices), deflated by the Consumer Price Index for All Urban Consumers: All Items Less Shelter (CPI-LS) from the Bureau of Labor Statistics. Time-to-sell is the median number of months on the sales market for newly completed homes from the New Residential Sales release (U.S. Census Bureau and U.S. Department of Housing and Urban Development). The homeowner vacancy rate is from the Housing Vacancies and Homeownership release of the U.S. Census Bureau. Panel B reports new stylized facts on home renovation lending, computed from the Home Mortgage Disclosure Act (HMDA) National Aggregate Report and restricted to loans with renovation as the stated loan purpose; the sample includes conventional, government-insured (FHA), and government-guaranteed (FSA, RHS, and VA) loans. The average renovation loan size is deflated by the CPI-LS. Each series is regressed on a constant and a linear time trend; the percentage change is computed as the difference between the 2012 and 2019 fitted values relative to the 2012 fitted value.

Panel A reports the joint behavior of prices, liquidity, and inventory during the recovery. The average house price rose by 39.61%, time-to-sell shortened by 25.96%, and the homeowner vacancy rate fell by 30.80% (Figure 2.1(a)–(c)). The simultaneous rise in prices and decline in time-to-sell indicates a substantial improvement in housing-market liquidity, while the decline in the vacancy rate reflects a contraction of for-sale inventory relative to buyer demand. These comovement patterns are consistent with those documented across the housing search-and-matching literature; see for example Diaz and Jerez (2013), Head et al. (2014), Ngai and Sheedy (2024), and Gabrovski and Ortego-Marti (2025).

Panel B reports two new facts on the parallel adjustment in renovation lending. Renovation loan originations rose by 57.41%, and the average renovation loan size rose by 18.48% (Figure 2.1(d)–(e)). Both moments co-move with the housing-market recovery in Panel A. The expansion of renovation lending occurs simultaneously with the rise in prices and the improvement in housing-market liquidity. The calibration in Section 2.3.2 disciplines both moments jointly with the housing-market moments in Panel A.

2.3.2 Calibration

We calibrate the model to the stylized facts in Section 2.3.1 in three steps. First, a subset of parameters is set externally, either to values from the literature, by normalization, or by holding cost ratios fixed across the two steady states. Second, the remaining parameters are calibrated internally so that the 2012 steady-state equilibrium reproduces a set of empirical moments characterizing the start of the recovery. Third, the structural shocks that drive the economy from the 2012 to the 2019 steady

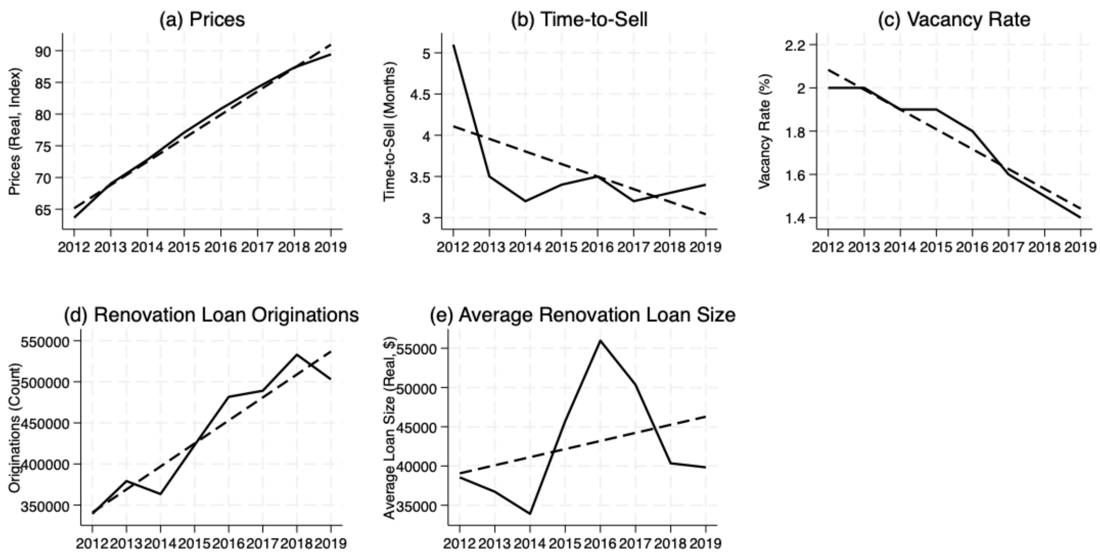


Figure 2.1: The 2012–2019 Housing Market Recovery

Notes: The figure plots the data (solid line) and fitted values (dashed line) for (a) the average house price (Case-Shiller National Home Price Index deflated by the CPI for All Items Less Shelter); (b) time-to-sell in months; (c) homeowner vacancy rate in percent; (d) renovation loan originations from the HMDA Loan Application Register, restricted to home improvement loans; and (e) the average renovation loan size in real dollars. Fitted values are obtained by regressing each series on a constant and a linear time trend over the 2012–2019 period.

state are recovered in Section 2.3.3 by matching the five percentage changes in Table 2.1. The model is solved at annual frequency throughout.

Table 2.2 reports both sets of parameters. Panel A lists the externally set parameters. The annual real interest rate $r = 0.035$ and the housing depreciation rate $\delta = 0.016$ are set to standard values from Ngai and Tenreyro (2014) and Van Nieuwerburgh and Weill (2010). The matching elasticity in the housing market $\alpha_m = 0.16$ follows Genesove and Han (2012), and the matching elasticity in the credit market $\alpha_f = 0.50$ follows Petrosky-Nadeau and Wasmer (2017). The buyer search-cost elasticity $\gamma = 2.00$ follows Gabrovski and Ortego-Marti (2021b). Flow utility from owning a low-type home is normalized to one in the 2012 steady state, $x = 1$. This is a standard normalization in housing search models, where all dollar-denominated costs and prices are then expressed in units of flow utility. The buyer search-cost scale $\bar{c} = 0.10$ is a separate normalization that pins down the level of the buyer's cost function. The bargaining power of the housing seller is set to $\beta = 0.5$ in the 2012 steady state, following Ngai and Sheedy (2020), and the bargaining power of the financier is set to $\eta = 0.4792$, following the internal calibration of Gabrovski and Ortego-Marti (2025). Both bargaining powers are treated as shocks rather than time-invariant parameters. They are allowed to adjust in the 2019 steady state to match the movements in the vacancy rate and the average renovation loan size, respectively.

Four cost ratios are held fixed across the 2012 and 2019 steady states. The renovation cost is set to $k^R/p_L = 0.20$. The seller search-cost ratio is $c^S/p_L = 0.051/\text{ATS}_{2012} \approx 0.121$, where the 5.1% realtor fee per transaction follows Ghent (2012) and $\text{ATS}_{2012} = 0.4208$ years is the 2012 average time-to-sell. The applicant search-cost ratio is $c^A/p_L \approx 0.036$, computed as the 2.5% per-transaction credit-market search cost from Ghent (2012)'s decomposition of the buyer's 8% expected search cost, divided by the 2012 average credit search duration $1/f(\phi)$. The financier search-cost ratio is $c^F/p_L = 0.0186$, set to the 2012–2019 average spread between Moody's Seasoned Aaa Corporate Bond yield and the 10-year Treasury yield, following Gabrovski and Ortego-Marti (2025). Holding these four ratios fixed across both steady states ensures that the expansion of renovation lending is identified through the credit-market matching and bargaining margins rather than through mechanical changes in the absolute level of search and renovation costs.

Table 2.2: Calibration

Parameter	Description	Value	Source / Target
Panel A. Externally set parameters			
r	Annual real interest rate	0.035	Ngai and Tenreyro (2014)
δ	Housing depreciation rate	0.016	Van Nieuwerburgh and Weill (2010)
α_m	Matching elasticity, housing market	0.16	Genesove and Han (2012)
α_f	Matching elasticity, credit market	0.50	Petrosky-Nadeau and Wasmer (2017)
γ	Buyer search-cost elasticity	2.00	Gabrovski and Ortego-Marti (2021b)
x	Flow utility, low-type home (2012)	1.00	Normalization
$\bar{c}$	Buyer search-cost scale	0.10	Normalization
β	Bargaining power, housing seller	0.50	Ngai and Sheedy (2020)
η	Bargaining power, financier	0.4792	Gabrovski and Ortego-Marti (2025)
Panel B. Internally calibrated parameters			
s	Separation rate	0.0951	Avg. tenure $\approx$ 9 years
μ	Utility from high-type	1.0838	$p_H/p_L = 1.15$
μ_H	Efficiency, housing market matching	2.3764	TTS = 0.4208
μ_f	Efficiency, credit market matching	0.6539	$1/f(\phi) = 0.6993$
k	Construction cost	10.96	HE condition
c^S	Seller flow search cost	1.4302	Realtor fee[a]
c^A	Applicant flow search cost	0.4213	Credit-market search cost[b]
c^F	Financier flow search cost	0.2195	Moody's Aaa-Treasury spread[c]
k^R	Renovation cost	2.3602	$k^R/p_L = 0.20$

Notes: All parameters are at annual frequency. The matching technologies are Cobb-Douglas: $M_H(b,v) = \mu_H\, b^{\alpha_m}\, v^{1-\alpha_m}$ and $M_C(\mathcal{A}, F) = \mu_f\, \mathcal{A}^{\alpha_f}\, F^{1-\alpha_f}$. Costs are reported in units of flow utility.

[a] $c^S/p_L = 0.051/\text{ATS}_{2012} = 0.1212$, following Ghent (2012)'s 5.1% per-transaction target.

[b] $c^A/p_L = 0.0357$, computed as the 2.5% per-transaction credit-market search cost from Ghent (2012) divided by the 2012 average credit search duration $1/f(\phi)$.

[c] $c^F/p_L = 0.0186$, set to the 2012–2019 average spread between Moody's Seasoned Aaa Corporate Bond yield and the 10-year Treasury yield, following Gabrovski and Ortego-Marti (2025).

The 2012 calibration targets characterize the U.S. housing market at the start of the recovery and discipline the internally calibrated parameters in Panel B. The utility multiplier of high-type homes is calibrated to $\mu = 1.0838$, so that the steady-state ratio of high- to low-type prices, p_H/p_L, equals 1.15. The housing-market matching efficiency $\mu_H = 2.3764$ is calibrated to deliver a 2012 time-to-sell of $\text{ATS}_{2012} = 0.4208$ years at $\theta = 1$, where the unit tightness follows the convention of equating time-to-buy and time-to-sell in Genesove and Han (2012). The credit-market matching efficiency $\mu_f = 0.6539$ is calibrated to deliver a 2012 credit-market matching rate $f(\phi) = 1.43$ per year, implying an average renovation loan search duration of 8.4 months. The magnitude of this target is informed by survey evidence on credit availability used in Gabrovski and Ortego-Marti (2025). The construction cost $k = 10.96$ is determined endogenously by the housing free-entry condition given the calibrated p_L and search costs.

The separation rate $s = 0.0951$ is set to match an average homeownership tenure of nine years following Diaz and Jerez (2013), computed as $s = 1/9 - \delta$. Two additional rate parameters govern the renovation block. The renovation downgrade rate $\delta_d = 0.10$ implies an average renovated occupancy spell of ten years before the home reverts to the low-quality pool through ordinary wear. The renovation opportunity rate $\lambda = 0.10$ does not have a direct empirical counterpart in standard sources. We set it as an internal calibration choice that delivers a non-degenerate applicant pool while maintaining a tractable credit-market block.[12]

To recover the structural shocks that drive the 2012–2019 transition, we vary five exogenous parameters jointly so that the model reproduces the five percentage changes in Table 2.1. The five free parameters are (i) the flow utility from a low-type home x, identified primarily by the average price target, (ii) the construction cost k, identified primarily by the time-to-sell target, (iii) the credit-market matching efficiency μ_f, identified primarily by the change in renovation loan originations, (iv) the

[12]The implied model-generated renovation rate, defined as the flow of completed renovations per low-type homeowner per year, $f(\phi)\mathcal{A}/h_L$, is approximately 11.5% in the 2012 calibration. We treat this as a model-implied object rather than a direct empirical target.

housing seller bargaining power β, identified primarily by the vacancy rate target, and (v) the financier bargaining power η, identified primarily by the change in the average renovation loan size. The four cost ratios and the separation rate are held fixed at their 2012 values, so that all variation across the two steady states is absorbed by the five free parameters above.

This identification structure extends Gabrovski and Ortego-Marti (2021b), who recover four shocks $\{\varepsilon, k, \mu_f, \beta\}$ against four targets in a model of mortgage financing. In their framework, the buyer's bargaining power in the housing and credit markets is assumed identical, collapsing β and η into a single parameter. Our framework maintains the distinction. The parameter β enters the housing-market free-entry condition and the housing Nash bargaining, while η enters the credit Nash bargaining and the financier free-entry condition. The two parameters therefore identify distinct moments, with β working through the vacancy rate and η working through the average renovation loan size, and the five-shock-five-target system is well-posed. The recovered shocks and their data targets are reported in Section 2.3.3.

2.3.3 Numerical Results

This section reports the quantitative properties of the calibrated model. We first describe the 2012 steady-state equilibrium and verify that the model reproduces the targeted moments. We then report the structural shocks recovered from the 2012–2019 transition. The counterfactual decomposition that quantifies the contribution of the renovation credit channel to the recovery is presented in Section 2.3.4.

Table 2.3 reports the equilibrium quantities at the calibrated 2012 steady state. The model reproduces the four targeted moments by construction. The high-to-low type price ratio p_H/p_L equals 1.15, time-to-sell is 0.4208 years (approximately five months), the homeowner vacancy rate is 4.33%, and the credit-market matching rate $f(\phi)$ is 1.43 per year, implying an average wait of 8.4 months for an applicant to be matched with a financier. The 2012 equilibrium prices are $p_L = 11.80$ and $p_H = 13.57$ in units of flow utility, and the average transaction price $\pi_L p_L + \pi_H p_H = 12.49$ serves as the benchmark for the +39.61% recovery in average prices through 2019. High-type vacancies account for $\pi_H = 38.80\%$ of the for-sale stock. This share governs the composition channel through which the renovation credit market transmits to housing-market liquidity in the counterfactual decomposition of Section 2.3.4.

Table 2.3: Calibrated equilibrium values.

Variable	Expression	Value
Housing market tightness	θ	1.000
Credit market tightness	ϕ	0.2091
Low-type price	p_L	11.80
High-type price	p_H	13.57
Average transaction price	$\pi_L p_L + \pi_H p_H$	12.49
Time-to-sell	$1/[\theta m(\theta)]$	0.4208
Vacancy rate	$(v_L + v_H)/\text{total}$	4.33%
Avg. renovation loan size	$\rho/(r+\delta)$	3.094
Renovation loan originations	$f(\phi)\mathcal{A}$	5.122

Notes. Prices and the loan size are reported in units of flow utility with $x = 1$ normalized. The targeted moments are the price ratio $p_H/p_L = 1.15$, time-to-sell, vacancy rate, and credit matching rate.

Table 2.4 reports the structural shocks $\{x, k, \mu_f, \beta, \eta\}$ recovered from the 2012–2019 transition, alongside the empirical target each shock is most directly identified by. The five shocks jointly reproduce the five percentage changes in Table 2.1, with all other parameters held fixed across the two steady states.

The housing demand x rises by 68.12%, which is large relative to the 39% recovered by Gabrovski and Ortego-Marti (2025) for the same period. The difference reflects our identification strategy. In our framework, x is recovered jointly with the housing seller bargaining shock β, which absorbs a fraction of the price recovery through the

Table 2.4: Size of recovered shocks, 2012–2019 baseline.

Shock		Data Target	
Variable	% Change	Variable	% Change
x	+68.12%	Average House Price	+39.61%
k	+40.09%	Time-to-Sell	−25.96%
μ_f	−21.53%	Renovation Loan Originations	+57.41%
β	−50.68%	Vacancy Rate	−30.80%
η	+86.90%	Average Renovation Loan Size	+18.48%

Notes. Table reports the size of the shocks to $\{x, k, \mu_f, \beta, \eta\}$ in the baseline model required to match the movements in the five empirical targets listed in the right panel.

bargaining wedge in the housing free-entry condition. The construction cost k rises by 40.09%, consistent with the empirical evidence on rising construction wages, materials prices, and land regulation over the recovery period, and well within the range of the 86% increase recovered by Gabrovski and Ortego-Marti (2025) for construction costs over the same period.

The two credit-market shocks move in opposite directions, and their combination drives the expansion of renovation lending. The credit-market matching efficiency μ_f falls by 21.53%, while the financier bargaining power η rises sharply from 0.4792 to 0.8956. At first glance the decline in μ_f may appear inconsistent with the 57.41% expansion in renovation loan originations. The resolution is that the sharp increase in η raises the financier's share of the credit match surplus, inducing a large expansion of financier entry. The applicant pool grows accordingly, and the originations flow $f(\phi)\mathcal{A}$ rises despite the lower matching rate per applicant. Credit-market tightness ϕ rises from 0.2091 to 1.9314, with the implied average credit search duration lengthening from 8.4 to 32.5 months.

A decline in credit-market matching efficiency over a credit expansion is not without precedent in this literature. Gabrovski and Ortego-Marti (2021b) recover a comparable decline in μ_f over the 1999–2006 mortgage boom and interpret it as the effect of looser lending standards drawing lower-quality applicants into the market, lowering the average match rate. The present setting is different in that originations-to-applications ratios in HMDA renovation data remained approximately stable over 2012–2019, suggesting that the recovered μ_f decline reflects the model's accommodation of a thicker applicant pool, driven by the η-induced rise in financier entry, rather than a deterioration in applicant quality. We interpret the rise in η as a reduced-form representation of post-crisis consolidation in the renovation lending market, with large national lenders gaining share at the expense of community banks and credit unions. Greater concentration is consistent with stronger lender bargaining position in setting loan terms.

The housing seller bargaining power β falls by half, from 0.50 to 0.2466. A decline in β shifts surplus from sellers to buyers in the housing Nash bargaining stage, lowering the markup over construction cost in the housing free-entry condition and slowing the rise in p_L relative to fundamentals. In the present recovery period, the post-crisis deleveraging and the gradual normalization of housing demand plausibly shifted the relative bargaining position toward buyers. We interpret the recovered β decline as the model's reduced-form representation of this broader shift.

2.3.4 Counterfactual Decomposition

To quantify the contribution of the renovation credit channel to the 2012–2019 recovery, we conduct a series of counterfactual experiments that hold the credit shocks at their 2012 values while leaving the housing-side shocks at their 2019 values. We focus on the credit shocks $\{\mu_f, \eta\}$ because they capture the renovation credit channel that distinguishes our framework from existing housing search models. We conduct three counterfactual exercises. Panel A holds both credit shocks at their 2012 values, Panel B holds the matching efficiency μ_f alone, and Panel C holds the credit bargaining shock η alone. In each case we re-solve the steady-state equilibrium and report the percentage change relative to the 2012 baseline. The difference between the full-recovery equilibrium and the counterfactual equilibrium measures the contribution of the credit shocks omitted in each scenario. Table 2.5 reports the results.

Table 2.5: Impact of credit shocks, baseline.

Panel A. No Change in Credit Shocks μ_f, η					
Variable	Price	TTS	Vacancy	Originations	Loan Size
Counter-factual	+39.13%	−9.34%	−8.87%	+91.08%	+40.40%
Panel B. No Change in Matching Efficiency μ_f					
Variable	Price	TTS	Vacancy	Originations	Loan Size
Counter-factual	+39.39%	−19.24%	−22.99%	+70.32%	+16.26%
Panel C. No Change in Credit Bargaining η					
Variable	Price	TTS	Vacancy	Originations	Loan Size
Counter-factual	+39.31%	−13.68%	−13.77%	+83.18%	+48.95%

Notes. Table reports the counterfactual changes in average house price, time-to-sell, vacancy rate, renovation loan originations, and average renovation loan size absent the indicated credit shocks. In Panel A both credit shocks μ_f and η are held at their 2012 values while the housing-side shocks x, k, and β take their 2019 values. Panels B and C repeat the exercise holding only the indicated credit shock at its 2012 value.

Two main findings emerge from the counterfactual exercises. First, the renovation credit channel has a negligible effect on the average house price. Panel A reports that, absent the credit shocks μ_f and η, the average price would still have risen by 39.13% over the recovery, only 0.48 percentage points below the actual 39.61% increase. The credit channel therefore accounts for 1.2% of the price recovery, with the remaining 98.8% attributable to the housing-side shocks $\{x, k, \beta\}$. This contrasts with Gabrovski and Ortego-Marti (2025), whose developer credit channel accounts for roughly half of the price recovery over the same period. In our framework, the demand shock x and the construction-cost shock k together account for nearly all of the price recovery, while the credit shocks contribute only marginally.

Second, the renovation credit channel is central to the recovery in housing-market liquidity. Panel A reveals that, absent the credit shocks, time-to-sell would have fallen by only 9.34% rather than the actual 25.96%, and the vacancy rate would have fallen by only 8.87% rather than the actual 30.80%. The credit channel therefore accounts for approximately 64% of the time-to-sell decline and 71% of the vacancy rate decline. The mechanism operates through the composition channel. The rise in the financier bargaining power η induces financier entry into the credit market, which shortens the search duration faced by applicants and raises the high-type homeowner value H_H. The higher H_H in turn raises the applicant value A, drawing more low-type homeowners into the credit market as applicants. The expanded applicant pool delivers a higher renovation flow, which translates into a larger stock of high-type homeowners and a larger flow of high-type vacancies into the for-sale market. The same increase in H_H also raises buyers' expected surplus from a match, inducing additional buyer entry into the housing market. As a result, housing-market tightness θ rises from 1.00 to 1.43, accelerating both time-to-sell and the depletion of the vacancy pool. This finding identifies a novel channel through which credit markets affect housing-market dynamics, a compositional channel of liquidity.

Panels B and C decompose the credit channel into its matching-efficiency and bargaining components. Reversing η alone (Panel C) yields counterfactual declines in time-to-sell and the vacancy rate of 13.68% and 13.77%, close to the 9.34% and 8.87% declines in Panel A in which both credit shocks are reversed. Reversing μ_f alone (Panel B) yields declines of 19.24% and 22.99%, closer to the full-recovery magnitudes of 25.96% and 30.80%. The contribution of η to the credit channel's effect on liquidity is therefore larger than that of μ_f within our framework.

To summarize, the counterfactual exercises support two main conclusions about the renovation credit channel. The channel has only a small effect on the average house price, in contrast to the substantial price effects of credit shocks documented in models of mortgage and construction financing. The channel, however, accounts for roughly two-thirds of the observed declines in time-to-sell and the vacancy rate, contributing substantially to the recovery in housing-market liquidity. These findings characterize a novel compositional channel of liquidity.

2.4 Conclusion

This chapter develops a search-and-matching model of the housing market in which homeowners finance renovation projects through a frictional credit market. The credit market in our setting finances renovations that upgrade low-type homes into high-type homes, generating a novel compositional channel through which credit conditions transmit to housing market outcomes. We calibrate the model to the U.S. housing recovery between 2012 and 2019 using stylized facts on the housing market combined with new facts on renovation lending computed from the HMDA. A counterfactual decomposition quantifies the contribution of the renovation credit channel to the recovery, with two main findings.

First, the renovation credit channel has a negligible effect on the average house price. In the absence of the credit shocks, the average price would still have risen by 39.13% over the recovery, only 0.48 percentage points below the actual 39.61% increase, so the credit channel accounts for only 1.2% of the price recovery. This stands in contrast with the quantitative findings of Gabrovski and Ortego-Marti (2025), whose developer credit channel accounts for roughly half of the price recovery over the same period. In our framework, the demand shock and the construction-cost shock together account for nearly all of the price recovery, while the credit shocks contribute only marginally.

Second, the renovation credit channel is an important driver of the recovery in housing-market liquidity. The credit channel accounts for approximately 64% of the observed decline in time-to-sell and 71% of the observed decline in the vacancy rate. The mechanism operates through the composition channel. The rise in the financier bargaining power η induces financier entry into the credit market, which shortens the search duration faced by applicants and raises the high-type homeowner value H_H. The higher H_H in turn raises the applicant value, drawing more low-type homeowners into the credit market and expanding the renovation flow. The same increase in H_H raises buyers' expected surplus from a match, inducing additional buyer entry. As a result, housing-market tightness rises and time-to-sell and the vacancy rate fall by substantially more than the housing-side shocks alone would have generated. This pattern identifies a novel mechanism through which credit markets affect housing-market dynamics. The contribution of η to this effect is larger than that of μ_f within our framework.

These findings position the renovation credit channel as a qualitatively distinct mechanism in the housing search-and-matching literature. The channel operates through composition rather than through the aggregate quantity of housing units. It contributes substantially to the recovery in housing-market liquidity while having only a small effect on housing prices, a pattern that differs from the developer and mortgage credit channels examined in the existing literature.

Several limitations of the analysis suggest natural directions for further work. First, the model treats buyers as financing house purchases without recourse to credit, abstracting from the role of mortgage frictions in the housing market. A natural extension is to introduce a second credit market for home purchase alongside the existing renovation credit market, which would allow the joint analysis of mortgage frictions, renovation frictions, and housing-market frictions, and their interaction over the housing cycle. Second, the renovation scale is fixed at k^R as a constant fraction of the low-type price. Endogenizing this scale through a collateral constraint that ties loan size to housing prices would introduce a price-credit feedback channel through which housing price growth relaxes the collateral cap, generating an additional amplification mechanism between credit market and housing market.

Chapter 3

The Collateral Channel of Renovation Loans

Abstract

Home equity is the largest asset on most household balance sheets, yet evidence on how collateral values shape household investment in the housing stock itself remains limited. This paper quantifies the causal effect of collateral-driven housing wealth shocks on renovation lending in the United States. Using loan-level data from the Home Mortgage Disclosure Act (HMDA) for 2011–2024, we adapt the empirical strategy of Chaney et al. (2012) to a household setting: we instrument MSA-level house prices with the interaction of national mortgage rates and local housing supply elasticity, and scale the resulting shocks by predetermined baseline collateral capacity constructed from the 2010 American Community Survey. This design generates ex-

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ogenous variation in pledgeable housing wealth at the MSA level. We find that for an MSA at the sample mean of log-collateral capacity (11.82), a 1% increase in instrumented house prices leads to an approximately $6,141 increase in the originated renovation loan amount, with effects concentrated in markets where households hold more pledgeable collateral at baseline. The effect is consistently stronger for originated loans than for the broader pool of applications, suggesting that house price appreciation operates primarily through the realized supply of credit. These findings extend the collateral channel from the corporate to the household setting and identify renovation lending as a key margin through which housing wealth shocks transmit to real investment in the housing stock.

3.1 Introduction

A central insight of modern corporate finance is that collateral values determine borrowing capacity, and that shocks to pledgeable assets can relax financing frictions and stimulate real investment. Chaney et al. (2012) show that U.S. corporations expand investment significantly when local real estate prices rise, as higher land values mechanically increase firms' debt capacity, a finding reinforced by evidence from international settings (Gan, 2007) and across alternative collateral measures (Cvijanović, 2014). The collateral channel is, by now, a well-established mechanism through which asset-price fluctuations transmit to firm-level real activity.

Households face a similar mechanism. Home equity is the largest asset most households own and the primary form of pledgeable wealth. Yet evidence on the household collateral channel has been concentrated primarily on consumption. Rising house prices allow homeowners to extract equity and finance spending (Aladangady, 2017; Case, Quigley, & Shiller, 2005; Mian & Sufi, 2011), while declining values tighten borrowing constraints and depress demand. What remains largely unexplored is the household counterpart to corporate investment, in the form of credit-financed expenditure that upgrades the household's own assets.[1] Renovation occupies precisely this position. While renovation spending generates immediate consumption value for the homeowner, it is also embedded in the physical housing stock and raises the future market value of the property, making it simultaneously a form of consumption and a form of investment. In this sense, renovation is the closest household analog to corporate investment in Chaney et al. (2012), namely collateral-financed expenditure that itself produces collateral, yet it has received comparatively little empirical attention.

The economic magnitude of this margin is large and growing. Total homeowner remodeling spending in the United States exceeded $500 billion in 2024.[2] Remodeling and repair expenditures grew by 25.3 percent over 2022–2023 alone, a period that coincided with U.S. household home equity reaching historic highs of nearly $30 trillion.[3] This co-movement is suggestive of a collateral-driven mechanism, but it is not causal evidence: house prices, household renovation demand, and credit supply all respond simultaneously to common macroeconomic shocks, making the underlying mechanism difficult to isolate without a credible identification strategy.

Understanding whether and how renovation credit responds to collateral values has implications that extend beyond the literature on housing wealth effects. Three considerations make this question particularly consequential. First, renovation is itself

[1]Existing studies of equity-based borrowing typically measure aggregate withdrawal without identifying how the funds are used, leaving renovation indistinguishable from other categories of spending. Loan-level HMDA data allow us to isolate credit explicitly designated for home improvement, a margin whose share of household borrowing has grown steadily over the past decade.

[2]Source: Joint Center for Housing Studies of Harvard University, *Leading Indicator of Remodeling Activity* (LIRA), October 2025 and January 2025 press releases. The LIRA measures aggregate annual spending on improvements and maintenance to owner-occupied homes.

[3]Source: Board of Governors of the Federal Reserve System, *Financial Accounts of the United States* (Z.1), Table B.101, Households and Nonprofit Organizations Balance Sheet; series "Owners' equity in real estate."

a quantitatively important form of fixed investment, shaping the long-run quality, durability, and energy efficiency of the U.S. housing stock, a margin that has gained renewed policy attention as the existing stock ages. Second, because renovation is financed predominantly through credit secured by the home itself, the strength of the collateral channel directly governs how shocks to mortgage rates, house prices, and credit conditions propagate into real investment in housing. Third, renovation offers a particularly clean empirical window on the household collateral channel: unlike consumption, which can be financed through many substitutable sources, renovation lending is mechanically tied to the underlying property and directly observable in loan-level data. Quantifying this channel, therefore, informs not only our understanding of housing wealth and household credit, but also the design of housing finance regulations and the targeting of housing quality and energy retrofit programs.

To identify the causal effect of collateral values on renovation credit, we combine loan-level data from the Home Mortgage Disclosure Act (HMDA) covering 2011–2024[4] with a quasi-experimental research design adapted from Chaney et al. (2012). Our identification strategy proceeds in two steps. First, we isolate exogenous variation in local house prices by instrumenting MSA-level price changes with the interaction of national 30-year mortgage rates and MSA-level housing supply elasticity from Saiz (2010). Intuitively, when national interest rates fall, housing demand rises everywhere, but the resulting price response is concentrated in MSAs where geographic and regulatory constraints prevent supply from adjusting. Second, we scale these instrumented price shocks by a predetermined measure of baseline collateral capacity, constructed at the MSA level from the 2010 American Community Survey.[5] This

[4]HMDA data are administered by the Federal Financial Institutions Examination Council (FFIEC). For collection years prior to 2017, data were processed and hosted by the Federal Reserve Board; from 2017 onward, by the Consumer Financial Protection Bureau (CFPB).

[5]This construction follows the empirical intuition in Chaney et al. (2012), who interact firms' predetermined real estate holdings, measured in 1993, with subsequent MSA level real estate price

interaction generates plausibly exogenous variation in pledgeable housing wealth, the key determinant of borrowing capacity in the collateral channel framework of Chaney et al. (2012). Borrower- and loan-level controls, together with MSA and year fixed effects, absorb residual heterogeneity, so identification ultimately rests on the differential response of renovation lending to common national interest-rate shocks across supply-constrained versus supply-elastic markets.

Three features of this identification strategy make it well-suited to isolate the household collateral channel. First, the instrument relies entirely on the interaction of two predetermined components: national mortgage rates, which absorb aggregate credit-market conditions through year fixed effects, and Saiz (2010) supply elasticity, which reflects long-run geographic and regulatory constraints on housing construction. Identification, therefore, comes neither from time-series variation in interest rates nor from cross-sectional differences in elasticity alone, but from their interaction, a source of variation that is unlikely to reflect reverse causality from local credit demand to house prices. Second, the instrument has a clear economic mechanism: supply-constrained markets see larger price responses to national demand shocks because new construction cannot absorb them. Third, by scaling instrumented price shocks by predetermined baseline collateral capacity, we obtain variation in pledgeable housing wealth rather than in house prices alone, which is the variable that directly governs borrowing capacity in the collateral channel. Together, these features help separate the causal effect of collateral values from the confounding factors that typically arise when local house prices, credit supply, and credit demand move together.

shocks to isolate the collateral channel for corporate investment. In our household setting, baseline collateral capacity is measured at the MSA level rather than the household level and is interacted with instrumented MSA house prices to capture variation in borrowing capacity through the collateral channel.

We find a sizable and statistically significant household collateral channel operating through renovation credit. In our preferred IV specification, a one-percent increase in instrumented house prices, interacted with baseline collateral capacity, leads to approximately a $6,141 increase in originated renovation lending for an MSA at the sample mean of log collateral capacity. The response is larger in markets where households hold more pledgeable housing wealth at baseline, indicating that the channel operates through the scale of pledgeable household wealth. Two patterns help clarify the mechanism: the effect is consistently stronger for originated loans than for the broader pool of loan applications, suggesting that house price appreciation operates primarily through the realized supply of credit rather than through latent borrower demand; and the estimated elasticity scales with baseline collateral capacity, consistent with the channel operating through the scale of pledgeable wealth that households can leverage. Neither unobserved demand shocks nor differential macroeconomic exposure alone can easily account for these patterns.

Our paper relates to four literatures. The closest precedent is the literature on the collateral channel (Chaney et al., 2012; Cvijanović, 2014; Gan, 2007), which documents how shocks to firms' real estate collateral relax financing frictions and stimulate corporate investment. We extend this mechanism from the corporate to the household setting, showing that renovation lending plays the household analog of corporate capital expenditure. The household setting also has a feature absent from the corporate case: renovation directly upgrades the collateral asset itself, opening up a self-reinforcing dimension that warrants further study. We also build on the literature on housing wealth and household behavior, which has focused primarily on consumption (Aladangady, 2017; Berger, Guerrieri, Lorenzoni, & Vavra, 2018; Case et al., 2005; Mian & Sufi, 2011). Our results extend this literature to investment in the housing stock itself. The distinction matters because renovation spending, unlike consumption, is durable and capitalized into property values, so the macroeconomic consequences of housing wealth shocks may differ from those identified in the consumption literature. A growing body of work studies household investment in the housing stock directly. Melzer (2017) shows that homeowners with negative equity reduce home improvement and maintenance spending by roughly 28 percent, consistent with debt overhang. Benmelech, Guren, and Melzer (2023) identify a "home purchase channel" through which housing transactions stimulate home-related spending and improvements. We complement this work by providing loan-level causal evidence that baseline collateral capacity, rather than only current equity or a recent home purchase, shapes the equilibrium volume of renovation credit and identifies a channel that operates alongside the debt overhang and home-purchase mechanisms. Finally, our findings have implications for the empirical literature on mortgage credit and house prices (Favara & Imbs, 2015; Mian & Sufi, 2009). By isolating renovation loans as a specific credit product and providing causal estimates of how local housing wealth shocks pass through to household credit, we provide magnitudes relevant to macroprudential policy: if renovation credit is highly collateral-sensitive, then loan-to-value regulations and housing-market interventions can affect not only credit volumes but also the long-run condition of the housing stock.

The remainder of the paper is organized as follows. Section 2 describes the data and sample construction. Section 3 develops the empirical strategy and identification assumptions. Section 4 presents the main results. Section 5 concludes.

3.2 Data and Sample Construction

This paper combines multiple datasets from national and local sources to construct a panel linking household borrowing behavior to local collateral shocks over 2011–

2024. The primary unit of observation is the individual loan, while the key identifying variations—housing price shocks and collateral capacity—are measured at the Metropolitan Statistical Area (MSA) level.

3.2.1 Sample Selection and Loan-Level Data

The core of our dataset consists of loan-level information from the Home Mortgage Disclosure Act (HMDA), as made available by the Consumer Financial Protection Bureau (2024) for collection years from 2017 onward and by the Federal Reserve Board for earlier years. These data provide granular borrower and loan characteristics, including application amounts, loan purposes, and lender identifiers.

From an initial pool of 3,683,794 loan applications across 66 unique MSAs, we restrict our primary estimation sample to originated loans to capture realized credit flows. This results in a final sample of 1,767,625 individual loan observations. To ensure the consistency of our financial variables over the sample period, all nominal values are deflated to constant 2009 dollars using the Consumer Price Index for All Urban Consumers (CPI-U) provided by the U.S. Bureau of Labor Statistics (2026). This adjustment allows our estimates to reflect real changes in credit volume rather than general price level fluctuations.

3.2.2 Identification and Local Market Variables

The identification of the collateral channel relies on the interaction of national credit shocks with structural local characteristics. We obtain house price measures from the Federal Housing Finance Agency (2024) House Price Index (HPI) at the MSA level to capture variation in housing wealth. To proxy for time-varying credit conditions, we utilize the national 30-year fixed mortgage interest rate from the Freddie

Mac Primary Mortgage Market Survey. Furthermore, we incorporate local housing supply elasticities from Saiz (2010) to account for the geographic barriers to housing expansion that govern how local markets respond to these aggregate shocks.

3.2.3 Baseline Capacity and Controls

To construct a measure of collateral capacity that is exogenous to the 2011-2024 sample period, we utilize the 2010 American Community Survey (ACS). We define market-level baseline collateral capacity as the product of the owner-occupied housing unit share and median home values within each MSA. Finally, we augment our model with additional borrower- and tract-level controls obtained from the ACS. Together, these sources provide a comprehensive panel of U.S. metropolitan housing markets, credit conditions, and demographic characteristics over the period studied.

To account for localized pandemic intensity, we incorporate county-level daily confirmed COVID-19 infection time-series data from the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE) Dong, Du, and Gardner (2020). We aggregate these daily reports to an annual frequency and map county-level observations to the MSA level to maintain geographic consistency with our house price and credit data. The resulting infection rate variable covers the 2020–2023 period, reflecting the years of active pandemic monitoring by JHU. Our primary control for local health shocks is the annual infection rate, defined as the total number of confirmed cases normalized by the total MSA population. This normalization allows us to capture the relative severity of the health crisis across different metropolitan markets while controlling for potential correlations between pandemic intensity and local housing demand.

3.2.4 Summary Statistics

Table 3.1 presents the descriptive statistics for our primary estimation sample, covering the period from 2011 to 2024.

Table 3.1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Real Loan Amount	3,360,614	121,254.10	714,209.80	880	2.91e+08
Real House Price Index	3,361,155	299.58	134.40	102.99	782.03
Collateral Capacity	3,265,036	145,274.80	57,469.73	54,707.43	361,775.20
Infection Rate/Population	1,041,539	0.08	0.05	0.00	0.19
Supply Elasticity	3,361,155	1.69	0.85	0.60	5.45
Interest Rate	3,361,155	4.41	1.13	2.96	6.81

3.3 Empirical Strategy

3.3.1 Construction of Collateral Capacity

A key challenge in estimating collateral effects on renovation loan amounts is identifying exogenous variation in collateral values that is not driven by local credit conditions. To address this concern, we follow the spirit of Chaney et al. (2012) by separating the baseline collateral holdings from the exogenous shocks to local house prices. Specifically, using the 2010 ACS as a predetermined benchmark, we construct a measure of *collateral capacity* at the MSA level as

$$\text{Collateral Capacity}_{m0} = \text{Owner-Occupied Share}_{m,2010} \times \text{Median Home Value}_{m,2010}, \tag{3.1}$$

where Owner-Occupied Share$_{m,2010}$ is the ratio of owner-occupied housing units to the total number of occupied housing units within an MSA m, Median Home Value$_{m,2010}$ is the median value of owner-occupied housing units for each geographic area and reflects the homeowners' estimates of their property's market value at the time of the survey. Owner-Occupied Share$_{m,2010}$ measure captures the prevalence of homeownership and, by extension, the portion of the local housing stock that can serve as collateral for household borrowing. Because home improvement loans are typically secured by owner-occupied properties, this variable serves as a key component of the baseline collateral capacity measure. Both Owner-Occupied Share$_{m,2010}$ and Median Home Value$_{m,2010}$ are held fixed across the 2011-2024 sample period, ensuring that it is predetermined with respect to contemporary loan market conditions. Collateral Capacity$_{m0}$ measures the average pledgeable housing wealth in each market at the baseline year. It is predetermined with respect to 2011–2024 HMDA outcomes and captures cross-sectional variation in collateral potential driven by baseline home values and owner-occupancy rates.

This construction is conceptually analogous to the "real estate holdings" measure in Chaney et al. (2012), where firm-level assets interacted with regional price shocks identify the collateral channel for corporate investment. In the household setting, Collateral Capacity$_{m0}$ plays an analogous role by providing the baseline exposure of a local housing market to price shocks, which, when interacted with instrumented house prices, isolates the causal effect of collateral value changes on renovation loan outcomes. Although this proxy abstracts from household-level debt and heterogeneity, it offers a tractable and predetermined measure of local pledgeable wealth.

We employ the natural logarithm of Collateral Capacity$_{m,2010}$ for several reasons. First, the distribution of housing wealth across MSAs is heavily right-skewed; the log transformation normalizes this distribution and reduces the influence of extreme outliers in large, high-value metropolitan markets. Second, this specification allows for a more intuitive interpretation of the interaction term in our empirical model. By using log-transformed variables, our coefficients can be interpreted as elasticities, capturing the percentage change in borrowing behavior resulting from a percentage change in available collateral.

3.3.2 Two-Stage Least Squares Estimation

The empirical strategy follows a two-stage least squares (2SLS) framework. Equation (3.2) specifies loan outcomes Y_{imt} at the borrower i level as a function of instrumented local house prices and borrower-level controls.

$$Y_{imt} \; = \; \alpha_m + \delta_t \; + \; \beta \left(cc_{m0} \cdot \hat{p}_{mt} \right) \; + \; \boldsymbol{X}_{imt} \boldsymbol{\Theta} + \varepsilon_{imt}, \tag{3.2}$$

where Y_{imt} denotes the loan amount for borrower i in MSA m and year t; cc_{m0} represents the natural logarithm of the baseline collateral capacity in MSA m, Collateral Capacity$_{m0}$, as defined in Equation (3.1); $\hat{p}_{mt}$ represents the instrumented log-transformed local house prices in MSA m and year t; $\boldsymbol{X}_{imt}$ denotes borrower- and tract-level covariates that account for observable heterogeneity in loan applications; α_m and δ_t denote MSA and year fixed effects, respectively.

We interact local house prices with baseline collateral capacity to capture the heterogeneous impact of housing wealth shocks. While regional price trends provide the time-varying shock, the extent to which these shocks are reflected in credit outcomes depends on the underlying collateral constraints of the local market. This interaction allows us to test whether the relationship between housing wealth and loan amounts is amplified in areas with higher initial collateral availability.

The coefficient β represents the marginal effect of the instrumented collateral-price shock on the dollar amount of originated loans. Specifically, β measures the change in the loan amount associated with a one-unit increase in the interaction between the log of the baseline collateral capacity and the log house price index. A positive and statistically significant β would indicate a dominant collateral channel, where a percentage increase in house prices leads to a larger level of credit provision, particularly in MSAs with higher baseline collateral capacity. Conversely, a negative β would suggest that increases in housing wealth substitute for external borrowing rather than stimulate it, leading to a reduction in the size of newly originated loans as households rely more on internal funds or lenders tighten credit when house prices rise.

The first stage instruments local house prices using the interaction of national mortgage rates and local land supply elasticity, as specified in the following equation:

$$p_{mt} \ = \ \alpha_m + \delta_t \ + \ \phi \left(ln(Elasticity_m \times IR_t) \right) \ + \ \boldsymbol{X}_{mt}\boldsymbol{\Pi} + u_{mt}, \tag{3.3}$$

where p_{mt} is the log house price index (HPI) for MSA m in year t; $Elasticity_m$ denotes the housing supply elasticity in MSA m, obtained from Saiz (2010); IR_t represents the national 30-year mortgage rate in year t; $\boldsymbol{X}_{mt}$ represents the local control variables; and α_m and δ_t denote MSA and year fixed effects, respectively.

In the first stage specification, the log house price index, p_{mt}, is the endogenous variable being instrumented. The excluded instrument is the log-transformed interaction of the national mortgage rate and local land supply elasticity, $\ln(Elasticity_m \times IR_t)$. This specification captures plausibly exogenous variation in local prices: when national interest rates fall, housing markets with lower supply elasticity experience stronger price increases. While mortgage rates are determined at the national level, their impact on local property values is heterogeneous and depends on geographic constraints. In MSAs where land supply is inelastic, shifts in national interest rates lead to significant price fluctuations because housing supply cannot easily adjust to changes in demand. In contrast, more elastic markets absorb these shocks through changes in construction volume rather than price. This interaction provides exogenous variation in housing wealth that is driven by macro-trends rather than idiosyncratic local credit demand, thereby satisfying the relevance condition. Furthermore, we log-transform the interaction term to ensure functional consistency with the log-transformed price index and to linearize the relationship between the geographic constraints and interest rate shocks. This transformation also mitigates the influence of skewed elasticity values, ensuring that the first-stage estimates are not driven by extreme outliers in the cross-section of MSAs.

The first stage coefficient ϕ represents the elasticity of local house prices with respect to the interest-rate-supply shock. Because both the house price index and the interaction term are log-transformed, ϕ captures the percentage change in the local property values associated with a one-percent change in the interaction of national mortgage rates and local land supply elasticity. A larger ϕ implies that price shocks are more pronounced in inelastic markets in response to national interest rate cycles. This interaction generates cross-sectional variation in housing wealth that is plausibly exogenous to local credit conditions, as it is driven by the intersection of national macro-trends and time-invariant geographic constraints.

Overall, the model allows us to interpret ϕ as the strength of local house price responses to national shocks, and β as the marginal impact of house price appreciation on renovation credit, conditioned on the level of baseline credit constraints.

3.3.3 Instrument Validity and Identification

Identification relies on exogenous variation in local house prices generated by the interaction of national mortgage rates and time-invariant differences in housing supply elasticity across MSAs. Because mortgage rates are set at the national level and land supply elasticity is a time-invariant geographic characteristic, this interaction produces plausibly exogenous variation in local housing wealth that is orthogonal to local credit demand conditions, conditional on MSA and year fixed effects.

Instrument relevance. The relevance condition requires that the interaction between national mortgage rates and local land supply elasticity significantly predicts local house price dynamics. Intuitively, declines in national interest rates increase housing demand nationwide, but the resulting price response varies systematically across MSAs depending on the ability of housing supply to adjust. In geographically constrained markets with low supply elasticity, demand shocks translate primarily into price appreciation, whereas in more elastic markets adjustment occurs largely through new construction. Consistent with this mechanism, the first-stage estimates show a strong and statistically significant relationship between the interest-rate-supply interaction and the local house price index. The corresponding first-stage F-statistics exceed conventional thresholds, alleviating concerns about weak instruments.

Exclusion restriction. The exclusion restriction requires that the interaction of national mortgage rates and local land supply elasticity affects loan outcomes only through its impact on local house prices. This assumption is supported by several features of the empirical design. First, mortgage rates vary only at the national level, and year fixed effects absorb any aggregate effects of interest rate changes on credit markets or lending conditions. Identification, therefore, comes from differential exposure to national rate shocks across MSAs with varying housing supply constraints, rather than from time-series variation in rates themselves. Second, land supply elasticity is predetermined and reflects long-run geographic constraints, making it unlikely to be correlated with contemporaneous local shocks to credit demand or lending policies. Conditional on MSA fixed effects, elasticity captures only time-invariant differences across regions, while the interaction isolates the heterogeneous price response to national shocks.

A potential concern is that national mortgage rate fluctuations could affect local loan outcomes through channels other than housing wealth in ways that vary systematically with land supply elasticity. One possibility is that interest rate changes directly alter aggregate credit supply by affecting lenders' funding costs, risk appetite, or underwriting standards. Such nationwide effects are absorbed by year fixed effects, so identification does not rely on time-series variation in interest rates. Another concern is that borrower loan demand or expectations may respond to interest rate cycles, or that local economic conditions such as income and employment may differentially co-move with national rate changes. These channels are mitigated by borrower- and tract-level controls, controls for local economic conditions, and MSA fixed effects, which absorb permanent cross-regional differences.

Additional concerns include the possibility that banks reallocate lending across space during interest rate cycles, that borrower composition or migration responds differentially in supply-constrained markets, or that baseline collateral capacity proxies for long-run differences in financial development. These channels would threaten identification only if national interest rate changes exert direct effects on loan amounts that differ systematically across MSAs according to land supply elasticity and operate independently of local house price movements. Given that land supply elasticity reflects physical and regulatory constraints on housing construction rather than financial or institutional features of credit markets, and that baseline collateral capacity is predetermined and enters the specification only through interactions with instrumented prices, such alternative channels are unlikely. Taken together, these considerations support the validity of the interest-rate–supply interaction as an instrument for local house prices in identifying the collateral channel.

3.4 Results

This section presents the main estimation results, highlighting how collateral shocks affect renovation loan amounts. Table 3.2 presents the OLS estimates, suggesting a positive correlation between home equity and loan amounts; however, these are likely biased downward due to measurement error in local house price indices. The coefficient on the interaction between baseline collateral capacity and local house prices is 5,533.07 and is statistically significant at the 10% level. Evaluated at the sample mean of log collateral capacity (11.82), a 1% increase in local house prices is associated with approximately a $654 increase in originated renovation loan amounts.

Table 3.3 presents the estimated impact of housing wealth shocks on renovation credit for originated loans. We focus primarily on originated loans because they represent the actual realization of credit supply. While applications reflect household demand, only originated loans result in a tangible change in household debt and subsequent investment in the housing stock.

Our preferred 2SLS specification in Column (6) accounts for borrower-level heterogeneity, COVID-related factors, loan characteristics, demographic controls, and fixed effects. The coefficient on the interaction term is 51,950.2 and is statistically significant at the 1% level. To put this in perspective, for an MSA at the sample mean of log collateral capacity (11.82), a 1% increase in instrumented house prices leads to approximately a $6,141 increase in originated renovation loan amounts.

The validity of this causal interpretation is supported by the first-stage diagnostics reported in Columns (1), (2), and (3). The excluded instrument, defined as the interaction between regional housing supply elasticity and national interest rates, is a strong negative predictor of local house price growth. This result is consistent with the idea that supply-inelastic housing markets experience larger price responses to macroeconomic shocks. The first-stage F-statistic of 10.33 further suggests that the instrument is sufficiently strong.

Table 3.2: The Impact of Housing Wealth on Renovation Credit
OLS Estimates
Loan Originated, 2011-2024

	(1)	(2)	(3)
$cc_{m0} \times \hat{p}_{mt}$	8,678.84*	5,558.56*	5,533.07*
	(4846.92)	(2876.68)	(2849.31)
Borrower-Level Controls	No	Yes	Yes
Loan Characteristics	No	Yes	Yes
Tract-level controls	No	Yes	Yes
COVID-19 Infection Rate	No	No	Yes
MSA Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	3,264,525	3,147,303	3,147,303

Notes: Borrower-level controls variables are log income and applicant race. Loan characteristic is loan type. Tract controls are tract minority share, log tract population, and log owner-occupied units. Standard errors are clustered at the MSA level.

*** p<0.01, ** p<0.05, * p<0.1.

Table 3.3: The Impact of Housing Wealth on Renovation Credit
Loan Originated
2011-2024

	IV (First Stage)			IV (Second Stage)		
	(1)	(2)	(3)	(4)	(5)	(6)
$cc_{m0} \times \hat{p}_{mt}$				74,319.47***	50,931.62***	51,950.2***
				(18866.68)	(14539.39)	(17058.35)
$\ln(Elasticity_m \times IR_t)$	-1.8***	-1.8***	-1.8***			
	(0.51)	(0.51)	(0.56)			
Borrower-Level Controls	No	Yes	Yes	No	Yes	Yes
Loan Characteristics	No	Yes	Yes	No	Yes	Yes
Tract-level controls	No	Yes	Yes	No	Yes	Yes
COVID-19 Infection Rate	No	No	Yes	No	No	Yes
MSA Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,264,525	3,147,303	3,147,303	3,264,525	3,147,303	3,147,303
F test	12.43	12.52	10.33			

Notes: Borrower-level controls variables are log income and applicant race. Loan characteristic is loan type. Tract controls are tract minority share, log tract population, and log owner-occupied units. Standard errors are clustered at the MSA level.
*** p<0.01, ** p<0.05, * p<0.1.

3.5 Conclusion

This paper quantifies a household collateral channel operating through renovation lending. Adapting the empirical strategy of Chaney et al. (2012) to a household setting, we combine loan-level HMDA data covering 2011–2024 with an instrumental-variables design that interacts national mortgage rates with local housing supply elasticity from Saiz (2010), scaled by predetermined baseline collateral capacity from the 2010 American Community Survey. The resulting variation in pledgeable housing wealth allows us to isolate the causal effect of collateral values on renovation credit, separately from the confounding factors that typically arise when house prices, credit supply, and credit demand move together.

Our main finding is that housing wealth has a sizable and statistically significant positive effect on renovation lending, with the response concentrated in markets where households hold more pledgeable collateral at baseline. The effect is consistently stronger for originated loans than for the broader pool of applications, indicating that collateral shocks operate primarily through the realized supply of credit rather than through latent borrower demand. Taken together, these results extend the collateral channel documented in the corporate finance literature to the household setting and identify renovation lending as a key margin through which housing wealth shocks transmit to real investment in the housing stock. Beyond their research implications, our estimates are also relevant for housing and credit policy. If renovation credit is highly sensitive to collateral values, then loan-to-value regulations and housing market interventions may affect not only credit volumes but also the long-run quality and maintenance of the housing stock.

A natural next step is to measure the asset-side counterpart of the channel we identify. Our analysis stops at the credit margin: we observe loan-level renovation lending but not the underlying property's purchase price, renovation timing, or subsequent resale value. Linking renovation credit to pproperty-leveltransaction histories using data sources such as CoreLogic, ATTOM, or deed records would allow for direct estimation of how renovation expenditures capitalize into future property values, and would provide a sharper test of the self-reinforcing dimension that distinguishes renovation from other forms of credit-financed household spending. We leave this exercise to future work.

Appendix

A. Additional Tables

Dependent Variable: Log of Loan Amount

Table 3.4: The Impact of Housing Wealth on Renovation Credit
Loan Originated
Dependent Variable: Log of Loan Amount
2011-2024

	OLS	IV (First Stage)	IV (Second Stage)
$cc_{m0} \times \hat{p}_{mt}$	0.022		0.33***
	(0.022)		(0.11)
$\ln(Elasticity_m \times IR_t)$		-1.8***	
		(0.51)	
Borrower-Level Controls	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes
Tract-level controls	Yes	Yes	Yes
COVID-19 Infection Rate	No	No	No
MSA Fixed Effect	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes
Observations	3,147,303	3,147,303	3,147,303
F test		12.52	

Notes: Borrower-level controls variables are log income and applicant race. Loan characteristic is loan type. Tract controls are tract minority share, log tract population, and log owner-occupied units. Standard errors are clustered at the MSA level.
*** p<0.01, ** p<0.05, * p<0.1.

Heterogeneity by Occupancy Type

To verify that our results operate through the household collateral channel rather than through alternative mechanisms, we examine heterogeneity by occupancy type. Loans are classified according to whether the property is intended to serve as a principal residence, second home, or investment property. This distinction is important because the collateral channel we study is fundamentally a household mechanism in which households borrow against home equity to finance household expenditure, and it applies most directly to owner occupied principal residences. Non-owner-occupied loans (second homes and investment properties) operate under different underwriting standards, face tighter LTV caps, and may respond to housing wealth shocks through different channels, such as rental yield, flip economics, or investor liquidity rather than household level spending decisions. By splitting the sample, we test whether the main effect is concentrated among homeowners, providing direct evidence that the household collateral channel drives our findings.

Table 3.5: The Impact of Housing Wealth on Renovation Credit
Loan Originated
2011-2024

	Owner-Occupied			Non-Owner-Occupied		
	OLS	IV (First Stage)	IV (Second Stage)	OLS	IV (First Stage)	IV (Second Stage)
$cc_{m0} \times \hat{p}_{mt}$	5,503*		50,451***	6,059.78**		56,611.26***
	(2878.65)		(14606.57)	(2488.65)		(14249.52)
$\ln(Elasticity_m \times IR_t)$		-1.8***			-2.35***	
		(0.5)			(0.61)	
Borrower-Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Tract-level controls	Yes	Yes	Yes	Yes	Yes	Yes
COVID-19 Infection Rate	No	No	No	No	No	No
MSA Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,002,675	3,002,675	3,002,675	141,360	141,360	141,360
F test		12.34			14.64	

Notes: Borrower-level controls variables are log income and applicant race. Loan characteristic is loan type. Tract controls are tract minority share, log tract population, and log owner-occupied units. Standard errors are clustered at the MSA level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

All Loan Applications (2018-2024)

Table 3.6: The Impact of Housing Wealth on Renovation Credit
All Loan Applications
2018-2024

	OLS		IV (First Stage)		IV (Second Stage)	
	(1)	(2)	(3)	(4)	(5)	(6)
$cc_{m0} \times \hat{p}_{mt}$	6,005.32*	3,836.817			33,617.28**	31,929.27**
	(3145.44)	(3529.31)			(13583.4)	(13519.35)
$\ln(Elasticity_m \times IR_t)$			-0.815***	-0.804***		
			(0.22)	(0.22)		
COVID-19 Infection Rate	Yes	Yes	Yes	Yes	Yes	Yes
Borrower-Level Controls	No	Yes	No	Yes	No	Yes
Loan Characteristics	No	Yes	No	Yes	No	Yes
Demographic Controls	No	Yes	No	Yes	No	Yes
MSA Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,112,407	2,031,618	2,112,407	2,031,618	2,112,407	2,031,618
F test			13.3	13.24		

Notes: Borrower-level control variables are log of income and Debt-to-Income (DTI) ratio, loan characteristics are occupancy type and loan type, demographic controls variables are age and race. Standard errors are clustered at the MSA level.
*** p<0.01, ** p<0.05, * p<0.1.

General Conclusion

This dissertation has examined renovation as a margin connecting housing markets, credit markets, and household collateral, asking how renovation interacts with search frictions, credit frictions, and collateral constraints, and what its aggregate consequences are. Three findings emerge. Chapter 1 develops a search-and-matching model with endogenous renovation and shows, using aggregate U.S. data, that renovation co-moves positively with prices, vacancies, and sales and negatively with time-on-market, and that housing-market variables track the data only when renovation responds endogenously. Chapter 2 embeds a frictional credit market for renovation financing and finds that, calibrated to the 2012–2019 U.S. housing recovery, the credit channel barely moves average prices yet accounts for roughly 64% and 71% of the declines in time-to-sell and the vacancy rate through a compositional channel of liquidity. Chapter 3 turns to loan-level HMDA data for 2011–2024 and, using an instrumental-variables design adapted from Chaney et al. (2012), identifies a sizable household collateral channel in which higher instrumented house prices raise originated renovation lending, with effects concentrated where households hold more pledgeable collateral.

Viewed as a whole, the three chapters trace a single mechanism across theory and data. The first two establish that renovation is a quantitatively important adjustment margin that shapes how prices, sales, vacancies, and liquidity co-move over the cycle, and that frictions in renovation financing reshape liquidity by altering the composition of the housing stock even when their effect on average prices is small. The third provides the empirical foundation linking the two, showing that household collateral values causally drive the very renovation credit that the models treat as central. The dissertation thus makes the case that renovation is a central margin in the housing market, shaping how prices, sales, and liquidity move over the cycle and how credit conditions are transmitted to them, with implications for housing and credit policy and for the quality and energy efficiency of the aging U.S. housing stock.

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