Home Construction Financing and Search Frictions in the Housing Market*

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Abstract

This paper studies the effects of financial frictions in construction on housing market dynamics. To this end, we build a search-theoretic model of the housing market in which there is endogenous entry of buyers and developers face credit constraints. We capture credit frictions by assuming that developers must search for financing before building a home à la Wasmer and Weil (2004). Our model explores a novel channel that links credit frictions faced by developers to the housing market. We calibrate the model to quantify the size of the credit channel during the 2012–2019 housing market recovery. Through a series of counterfactuals, our model predicts that the credit channel had a large impact on housing liquidity, construction, and the vacancy rate. Furthermore, it accounts for around half of the rise in prices during the 2012-2019 housing market recovery.

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1 Introduction

Understanding housing market dynamics is a crucial question in economics. The US homeownership rate is higher than 60%, and for most households home equity is one of the largest components of their net worth—home equity is around a third of households' equity. In addition, residential homes are a very illiquid asset. It takes on average 6 months to sell a house in the US and we observe large amounts of price dispersion for houses with similar characteristics (Kotova and Zhang, 2020). Moreover, a salient feature of the housing market is that construction firms are largely indebted, with a debt-to-equity ratio of around 94%. This fact suggests that construction, a key driver of housing supply, faces substantial credit frictions. Despite the importance of credit constraints for construction, little is known about how credit frictions affect house prices and liquidity.

To fill this gap in the literature, this paper studies the effect of credit frictions faced by developers on the housing market, with an emphasis on house prices, time-to-sell (a measure of liquidity), sales, construction and houses for sale, all of which are key variables of the housing market. To do so, we build a model with search frictions in the housing market and in which developers face credit constraints. More specifically, developers must secure financing in order to build a home. We model these credit frictions by assuming search and matching frictions in the credit market (Gabrovski and Ortego-Marti, 2021a; Petrosky-Nadeau and Wasmer, 2017; Wasmer and Weil, 2004).[1] In addition, we assume search frictions in the housing market in the spirit of Pissarides (2000) to capture that buying and selling houses is a time-consuming and costly process. Search frictions provide a mechanism that generates liquidity in the housing market. Another key feature of the model is an endogenous entry decision of buyers and sellers as in Gabrovski and Ortego-Marti (2019). This endogenous entry of both buyers and sellers allows the model to match the co-movement of house prices, time-to-sell, sales and house for sale, and generates an upward-sloping Beveridge Curve, consistent with the stylized facts in the housing market (Gabrovski and Ortego-Marti, 2019).

Our model uncovers a novel channel that links credit frictions faced by developers to the housing market. In the model, credit shocks affect entry of new housing and the cost of financing new construction. In turn, outcomes in the credit market affect the equilibrium in the housing market because they affect the surplus from matching in the housing market and, therefore, the entry of new housing and buyers. Similarly, shocks to the housing market affect the equilibrium time-to-sell (i.e. housing market tightness) and the surplus from matching in the housing market, which determines the entry decision of both banks and developers, and influences the terms of trade in the credit market.

[1] There is a large body of empirical evidence that finds significant amount of search in credit and financial markets, even for homogenous products and among homogenous groups of consumers, such as conforming mortgage loans, insurance policies and hedge funds. See section 2.1 for a discussion of this empirical evidence.

In order to gauge the quantitative magnitude of this credit channel, we calibrate the model and decompose the relative contribution of housing and credit market shocks to the observed housing market recovery in the U.S. during the 2012–2019 period. Construction of new homes dramatically dropped during the Great Recession, and only experienced a modest increasing trend during the recovery. It is often argued in the literature and by market observers that the low levels of construction during the post-recession played an important role in explaining the dynamics of the housing market after the Great Recession. Our mechanism allows us to quantify the role of credit frictions faced by developers during the housing market recovery.

Our calibrated model is able to exactly match a number of targeted moments, including the observed increase in prices, sales, construction costs and the fraction of new home sales, as well as the observed decline in time-to-sell. Importantly, the model also matches well two key non-targeted moments: the observed decline in the vacancy rate and the increase in housing construction. These results give us confidence that our mechanism captures well the housing market recovery during the 2012–2019 period. Overall, our calibration is consistent with the following picture of the housing market recovery: higher construction costs led to an increase in prices, but this was met with a simultaneous increase in the demand for housing that lead to more buyers in the market, and subsequently lower vacancy rates and time-to-sell. At the same time, higher construction rates had a compositional effect, with a higher fraction of sales coming from new construction. Moreover, our model allows us to back out the implied increase in the cost to build a new home and list it for sale. This is the total vacancy cost for newly build homes which consists of the construction cost and the cost due to financial frictions. We find that the total vacancy cost increased by about 45% during the period. Yet, the fraction of the cost due to financial frictions remained constant at about 72%. Moreover, the fraction of the financial cost borne by the developer (vs. the financier) also remained relatively constant at about 72%.

We then use the calibrated model to simulate a series of counterfactuals. More specifically, we shut down shocks to the credit market to quantify the role of credit frictions in accounting for the stylized facts during the housing market recovery. Absent shocks to the credit market, construction more than triples due to lower total costs of creating a vacancy. The increase in construction raises the vacancy rate by about two thirds, but also leads to about twice as long time-to-sell, instead of the observed drop in time-to-sell. This suggests that the large increase in vacancies is not matched by a similar increase in buyers, which is why time-to-sell rises. Interestingly, and perhaps intuitively, in the absence of credit shocks prices experience a more modest increase relative to the data. Our model predicts that about half of the build up in prices during the recovery was due to credit shocks.[2] Overall, our results suggest that credit frictions had large impact on liquidity, construction and vacancies, and that they can account

[2]More precisely, absent these credit shocks the increase in prices would have been half the size.

for about half of the rise in prices during the housing market recovery 2012-2019.

Related literature. Following the seminal work in Arnott (1989) and Wheaton (1990), a large number of papers have used search models à la Diamond-Mortensen-Pissarides to study the housing market. Search frictions provide a useful framework to understand the comovement of house prices, time-to-sell, sales and houses for sale. To understand the dynamics of house prices and liquidity in the housing market, the literature captures search frictions in the housing market either using a matching function (Arefeva, 2020; Burnside *et al.*, 2016; Diaz and Jerez, 2013; Gabrovski and Ortego-Marti, 2019, 2021a,b,c; Garriga and Hedlund, 2020; Genesove and Han, 2012; Guren, 2018; Head *et al.*, 2014, 2016; Kotova and Zhang, 2020; Novy-Marx, 2009; Piazzesi and Schneider, 2009; Piazzesi *et al.*, 2020; Smith, 2020), or by considering changes in the reservation value of houses (Krainer, 2001; Ngai and Sheedy, 2020; Ngai and Tenreyro, 2014). Han and Strange (2015) provides an extensive review of the literature on search frictions in the housing market.[3]

Among the papers mentioned above studying models of the housing market with search frictions, only Gabrovski and Ortego-Marti (2019, 2021a,b) and Head *et al.* (2014, 2016) focus on construction and the entry decision of developers. However, none of these papers consider the impact of credit frictions faced by developers on the housing market. Our paper is also related to a number of papers that study the housing market with search frictions and financially constrained households. Guren and McQuade (2018) and Hedlund (2016) study the linkages between housing prices, sales, and foreclosures, whereas Head *et al.* (2016) study the link between the size of the seller's outstanding mortgage, housing prices and time-to-sell. Garriga and Hedlund (2020) focus on the 2006-2011 housing bust and its spillover to consumption in an environment with search frictions in the housing market and mortgage contracts. Gabrovski and Ortego-Marti (2021a) study mortgages and credit constraints on housing prices, liquidity and mortgage debt during the built-up in housing prices prior to the housing bust. All these papers focus on the credit frictions captured by mortgages, which may be viewed as determinants of the demand side of the housing market. By contrast, this paper complements these findings by analyzing how credit frictions affect the supply side of the housing market. Surprisingly, the literature has not exerted as much effort in understanding how credit frictions affect housing supply, and their implications for house prices and liquidity. To our knowledge this is the first paper to study the effects of credit frictions faced by developers (a key determinant of housing supply) on housing market outcomes in a theoretical search environment. We build on our novel framework to understand the effect of credit frictions on the supply side on the housing market, especially on housing prices, liquidity and construction.

[3]To a lesser extent, our paper is also related to a big literature on housing and macroeconomics without search and matching frictions. Papers in this literature include Davis and Heathcote (2005), Gelain, Lansing and Natvik (2018) and Kydland, Rupert and Sustek (2016), among others. For a recent survey, see Piazzesi and Schneider (2016).

Finally, our paper is broadly related to the seminal work in Wasmer and Weil (2004) (see also Petrosky-Nadeau and Wasmer (2017)). As in Gabrovski and Ortego-Marti (2021a), we follow a similar approach and model credit frictions as search and matching frictions in the credit market. This approach captures the idea that it takes time for banks and developers to form a match, and that there is free entry on both sides of the market (another key feature is that prices are determined by bargaining). Our approach to credit frictions in the spirit of Wasmer and Weil (2004) is complementary to models with credit frictions in the spirit of Kiyotaki and Moore (1997).

The paper proceeds with a description of the credit and housing market. After describing the environment, we characterize the equilibrium. Next, we conduct a quantitative exercise to gauge the size of the credit channel and to assess the role of credit frictions in construction during the housing market recovery 2012-2019.

2 A model of the housing market

We begin with a description of the environment. Time is continuous. Agents are infinitely lived, risk-neutral and discount the future at a rate r. There are four types of agents in the economy: households, developers, financiers and real estate agents. Households are either homeowners, buyers (i.e. do not own a home but are actively searching for a house to purchase), or they can choose not to participate in the housing market. Developers have the technology to build new housing, but they must first secure financing for their construction project from a financier (or bank). We capture these frictions in the credit market by assuming search and matching frictions in the spirit of Wasmer and Weil (2004), Petrosky-Nadeau and Wasmer (2017) and Gabrovski and Ortego-Marti (2021a). Search in the credit market is costly and time-consuming for both developers and financiers. Once a developer meets a financier and a match is formed, the financier covers the construction costs. In exchange, the developer starts paying a financing fee until she finds a buyer for the newly built house, at which point the developer repays the loan principal.

The housing market is also subject to search and matching frictions. It takes time for buyers to find a suitable house and for sellers to find a buyer. Buyers search for houses with the help of a realtor, who charges a fee for her services. Although assuming realtors is a realistic characterization of housing markets, it is worth noting that results are unchanged if buyers search by themselves without the help of a realtor.[4] There are two types of sellers. In addition to newly built houses sold by developers, homeowners receive a separation shock at an exogenous rate. Once a separation shock occurs, the homeowner puts her house for sale. As a result, sellers are either homeowners who post an *existing* house for sale or developers selling

[4] See Gabrovski and Ortego-Marti (2019) for details.

new houses. Upon forming a match, the buyer and the seller bargain over the house price using Nash Bargaining. Existing houses and newly built housing are identical, although their prices may differ because of bargaining, as we show later on. We assume that bargaining is sequential, i.e. when a buyer and a developer meet they take the financial contract between the developer and the financier as given. Finally, there is free entry of buyers, developers and financiers. Free entry of buyers and sellers (through the entry of developers described above) is necessary to match housing market dynamics, i.e. that house prices are positively correlated with vacancies and sales, but negatively correlated with time-to-sell, and in particular the positive correlation between buyers and vacancies (Gabrovski and Ortego-Marti, 2019). We use the terms vacancies and houses for sales interchangeably.

2.1 The credit market

Obtaining financing for a construction project is costly, time consuming, and uncertain. Similar to Gabrovski and Ortego-Marti (2021a), Petrosky-Nadeau and Wasmer (2017) and Wasmer and Weil (2004), we capture credit market frictions by assuming search and matching frictions in the credit market and free entry of both developers (borrowers) and financiers (lenders). Prices in the market, which include loan repayments and a financing fee, are negotiated using Nash bargaining (Nash, 1950; Rubinstein, 1982). This flow approach to the credit market, and the view that credit arrangements are the result of search frictions, is well supported empirically and has been studied in den Haan *et al.* (2003) and Dell'Ariccia and Garibaldi (2005), among others.[5] This is particularly true for construction lending, which relies mostly on local markets/lenders (Ambrose and Peek, 2008), most likely due to the fact that, unlike mortgage markets, construction lending has not experienced a significant development of secondary markets.[6]

Let $\mathcal{D}$ and $\mathcal{F}$ denote the measure of developers and financiers. The number of matches between developers and financiers is given by a matching function in the credit market $M^C(\mathcal{D}, \mathcal{F})$. The matching function satisfies the usual properties: it is increasing in each of its arguments,

[5] More broadly, a large literature in IO and finance finds strong evidence of search frictions in financial, insurance, and credit markets, and models these markets with search frameworks in the spirit of Stigler (1961). For very homogeneous products and consumers, such as S&P 500 mutual funds or conforming mortgage loans, the literature finds high levels of price/rate dispersion. Many studies also find direct evidence that buyers contact several retailers/lenders and receive several quotes. Both of these sources of evidence strongly point to search frictions. Among others, see Allen *et al.* (2014a,b, 2019) for search in the mortgage market, Hortaçsu and Syverson (2004) for S&P 500 mutual funds, Sorensen (2001) for health services/insurance, Honka (2014) for auto insurance, and the references therein. These studies focus on markets with very homogeneous products and in some cases on a very homogeneous set of consumers (for example, conforming mortgage loans and buyers with similar credit scores and characteristics). Construction loans are in general much riskier, given that there is uncertainty on whether construction will be completed and each construction project has unique characteristics. Search frictions are more prevalent in such markets.

[6] Ambrose and Peek (2008) find large and significant effects of credit access for home construction.

concave and exhibits constant returns to scale. Let $\phi \equiv \mathcal{D}/\mathcal{F}$ denote the credit market tightness. The credit market tightness determines the rate at which developers and financiers meet each other. Developers match with a financier at a Poisson rate $q(\phi) \equiv M^C(\mathcal{D}, \mathcal{F})/\mathcal{D} = M^C(1, \phi^{-1})$, while financiers meet developers at a Poisson rate $\phi q(\phi) = M^C(\mathcal{D}, \mathcal{F})/\mathcal{F} = M^C(\phi, 1)$. Upon meeting, the developer and the financier bargain over the financing contract. The financier finances the construction cost k of building a new house. These construction costs capture all costs incurred in building a home, and includes for example land costs, planning, permitting, converting land use, costs associated with satisfying regulatory restrictions and building the structure itself. In exchange for financing construction costs k, the developer makes repayments ρ until she sells the house. Upon selling the house, the developer repays the loan principal k.

Both developers and financiers incur search costs c^D and c^F respectively while searching for a match. The developer's flow costs c^D include the costs of searching for potential lenders, gathering information on loan rates and preparing the documentation required for the loan application. The financier flow costs c^F include costs involved in attracting applicants, advertising and screening of applications. Although not essential, these costs may also include the costs associated with holding liquid assets for the purposes of lending, similar to overhead costs in Kashyap *et al.* (2002).[7]

2.2 The housing market

Similar to the credit market, we assume search and matching frictions in the housing market to capture that it takes time for buyers to find a house and for sellers to match with a suitable buyer. As in Gabrovski and Ortego-Marti (2019, 2021a), buyers require the services of a representative realtor to search for houses. Let b denote the measure of buyers searching for a house. Searching for houses 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 given that the realtor's revenue from servicing b buyers equals $bc^B(b)$, profit maximization implies that $c^B(b) = \bar{c}b^{\gamma}$. This approach to realtor services is consistent with the empirical real estate literature (Gabrovski and Ortego-Marti, 2019).

For simplicity of exposition, we assume that all search activities are done by the realtor on the buyer's behalf, and that the buyer pays the realtor a fee as compensation for her search efforts. In reality some of these search activities are done by buyers themselves, with search costs increasing in the measure of buyers searching due to congestion externalities. This alternative formulation leads to the same equilibrium. An important feature of the realtor's fee is that

[7] See Gabrovski and Ortego-Marti (2021a) for a review of some of the findings in the finance literature on the relationship between banks' holdings of liquid assets and their ability to extend loans.

it is increasing in the measure of buyers b, which is what induces endogenous movements in the entry of buyers. Intuitively, as in any model with entry, some cost or price must increase as more agents enter the market to feature endogenous entry. With a constant or decreasing $c^B(b)$, either all agents are buyers or no agent enters the housing market.

On the seller side, there are two types of vacancies, existing or new housing. First, some homeowners are hit with a separation shock at an exogenous rate s and put their house for sale. We refer to this type of houses as *existing* housing. *New* housing corresponds to houses newly built by developers. Both existing and new housing are identical, although they may sell at different prices due to bargaining, as we elaborate in section 2.4. Let v^N denote the measure of new houses for sale, v^E the measure of existing houses for sale, and $v \equiv v^E + v^N$ the overall measure of houses for sale or vacancies. Sellers posting a house for sale incur flow vacancy costs c^S.

We use the matching function approach in Pissarides (2000) to model search frictions. The number of matches in the housing market is given by the matching function $M^H(b, v)$, which satisfies the usual assumptions: increasing in each argument, concave and displays constant returns to scale. Given this matching function, buyers find a house at a Poisson rate $m(\theta) \equiv M^H(b, v)/b = M^H(1, \theta^{-1})$ and sellers find a suitable buyer at a rate $\theta m(\theta) = M^H(b, v)/v = M^H(\theta, 1)$, where $\theta \equiv b/v$ is the housing market tightness. Intuitively, as market tightness θ increases, vacancies become relatively more scarce, so buyers find houses at a slower rate, while it becomes easier for sellers to find a buyer.

As most papers in the literature, we do not model the rental market, given the empirical evidence that both markets are different and can be treated separately. Glaeser and Gyourko (2007) find that rental and owner occupied homes have very different characteristics and that there is no arbitrage between both types of homes. In addition, Bachmann and Cooper (2014) find that most flows are within each rental/owner category, flows from the owner to rental segment are acyclical, and turnover is unrelated to vacancies in the rental market. Consistent with our framework of endogenous entry of buyers, most fluctuations occur in the rental to owner occupied flow (i.e. entry of buyers).

2.3 Bellman equations

Let V_0 denote the value function of a developer searching for financing and V_1 the value function of a developer who has built a new home after securing funds from the financier, and is now searching for a buyer for the newly built house. Similarly, let F_0 denote the value function of a financier searching for a developer, and F_1 the value function of a financier who has entered a lending arrangement with a developer.

The value functions of financiers and developers when they are trying to form a match satisfy the following Bellman equations

$$rV_0 = -c^D + q(\phi)(V_1 - V_0), \tag{1}$$

$$rF_0 = -c^F + \phi q(\phi)(F_1 - k - F_0). \tag{2}$$

Equation (1) captures that the developer incurs search costs c^D while searching for a financier to fund her construction project. At a rate $q(\phi)$, she is matched with a financier and secures financing, which leads to a net gain $V_1 - V_0$. Similarly, from (2) the financier incurs a search flow cost c^F. At a rate $\phi q(\phi)$ she finds a developer searching for financing and a match is formed. At that point, the financier finances the construction cost k and becomes a financier with an active lending arrangement, which has a value F_1.

Similarly, the value functions of the financier and the developer upon entering the financial arrangement satisfy the Bellman equations

$$(r + \delta)V_1 = -\rho - c^D + \theta m(\theta)(p^N - k - V_1), \tag{3}$$

$$(r + \delta)F_1 = \rho - c^F + \theta m(\theta)(k - F_1), \tag{4}$$

where p^N denotes the price of a newly built house. The developer makes payments ρ to the financier and incurs search costs until she sells the new house. Upon finding a buyer, which happens at a rate $\theta m(\theta)$, the developer receives the price p^N and pays off the loan principal k. From (4), the financier receives payments ρ until the developer finds a buyer, which happens at a rate $\theta m(\theta)$. Once the developer finds a buyer, the financier recoups the loan principal k. Let V^E denote the value function of a homeowner posting her existing house for sale. The value function V^E satisfies the Bellman equation

$$(r + \delta)V^E = -c^S + \theta m(\theta)(p^E - V^E). \tag{5}$$

A seller incurs search costs c^S. At a rate $\theta m(\theta)$ she finds a buyer and receives a net gain $p^E - V^E$.

On the buyer side. Buyers can be matched with both types of houses, new and existing. Let π denote the share of existing houses among houses for sale, i.e. $\pi \equiv v^E/v$.

$$(r + \delta)H = \varepsilon + s(V^E + \max\{B, 0\} - H), \tag{6}$$

$$rB = \max\{0, -c^B(b) + m(\theta)[\pi(H - p^E - B) + (1 - \pi)(H - p^N - B)]. \tag{7}$$

Homeowners derive utility ε from owning a home. When a separation shock arrives at a rate s, they become a seller of an existing house and can choose to become a buyer, which yields a net gain $V^E + \max\{B, 0\} - H$. If they choose to participate in the market, buyers incur flow costs $c^B(b)$. At a rate $m(\theta)$ they are matched with a house. With probability π the house is an existing house and the match carries a net gain $H - p^E - B$, whereas with probability $1-\pi$ the house is newly built and the match yields a net surplus $H - p^N - B$.

2.4 Bargaining

In both the credit and housing markets, the surplus from matching is split according to Nash Bargaining (Nash, 1950; Rubinstein, 1982). Similar to Gabrovski and Ortego-Marti (2021a) and Petrosky-Nadeau and Wasmer (2017), we assume that bargaining is sequential, i.e. sellers of newly built houses and buyers take the financial contract between the developer and the financier as given.

Consider bargaining in the credit market. Let $S^D = V_1 - V_0$ and $S^F = F_1 - k - F_0$ denote the surplus of a developer and the financier when they form a match. The repayments ρ solve the following Nash Bargaining problem

$$\rho = \arg\max_{\rho} (S^D)^{\eta}(S^F)^{1-\eta}, \tag{8}$$

where η is the developer's bargaining strength. In the housing market, let $S^{BE} = H - B - p^E$ and $S^{BN} = H - B - p^N$ denote the buyer's surplus from an existing and newly built house respectively. Sellers' surplus from selling an existing and newly built house are denoted $S^{SE} = p^E - V^E$ and $S^{SN} = p^N - k - V_1$. House prices of newly built and existing houses p^i, for $i = N, E$, are the solution to the Nash Bargaining problem

$$p^i = \arg\max_{p^i} (S^{Si})^{\beta}(S^{Bi})^{1-\beta},\ i = N, E, \tag{9}$$

where β denotes the seller's bargaining strength in the housing market.

The first order conditions to the above two bargaining problems give the following sharing rules

$$\beta S^{Bi} = (1-\beta)S^{Si}, i = N, E, \tag{10}$$

$$\eta S^F = (1-\eta)S^D. \tag{11}$$

Let $S^i \equiv S^{Bi} + S^{Si}$, for $i = N, E$, denote the total surplus of a match with a new house ($i = N$) and an existing house ($i = E$) in the housing market. Similarly, let $S_0 = S^F + S^D$ denote the total surplus of a match in the credit market. The Nash Bargaining rules (10) and (11) imply the following conditions

$$
\begin{aligned}
S^{Si} &= \beta S^i, \text{ for } i = N, E,\\
S^{Bi} &= (1-\beta) S^i, \text{ for } i = N, E,\\
S^D &= \eta S_0,\\
S^F &= (1-\eta) S_0.
\end{aligned} \tag{12}
$$

Intuitively, with Nash Bargaining each party gets a share of the surplus, where the share equals their bargaining weight.

3 Equilibrium

To characterize the equilibrium, we begin by deriving the entry conditions for buyers, sellers and financiers. We then solve for the equilibrium prices in the housing and credit markets from bargaining. Finally, we use the laws of motion to derive the distribution of new and existing houses for sale, as well as the measure of developers.

In the credit market, free entry of financiers and developers imply $V_0 = F_0 = 0$. Substituting the free entry of developers $V_0^N = 0$ into (1) gives the Housing Entry (HE) condition

$$V_1^N = \frac{c^D}{q(\phi)}. \tag{13}$$

Similarly, free entry of financiers $F_0 = 0$ combined with (2) gives the Credit Entry (CE) condition

$$F_1 = \frac{c^F}{\phi q(\phi)} + k. \tag{14}$$

The two entry conditions above capture that developers and financiers keep entering the market until their expected costs equal the value from matching. Developers' expected costs include the search costs c^D for the average duration of search $1/q(\phi)$. For financiers, their costs also include the size of the loan k, in addition to their expected search costs $c^F/(\phi q(\phi))$. Rearranging the Bellman equations (3) and (4), together with free entry, gives

$$F_1 = \frac{\rho - c^F + \theta m(\theta) k}{r + \delta + \theta m(\theta)}, \tag{15}$$

$$V_1 = \frac{-\rho - c^D + \theta m(\theta)(p^N - k)}{r + \delta + \theta m(\theta)}. \tag{16}$$

The above equations imply that the total surplus in the credit market S_0 is given by

$$S_0 = \frac{-c^F - c^D + \theta m(\theta) p^N}{r + \delta + \theta m(\theta)} - k. \tag{17}$$

Substituting the above equation into (13) and (14), together with Nash Bargaining, implies the following HE and CE conditions

$$\text{HE:} \quad \frac{c^D}{q(\phi)} = \eta \left(\frac{-c^F - c^D + \theta m(\theta) p^N}{r + \delta + \theta m(\theta)} - k \right), \tag{18}$$

$$\text{CE:} \quad \frac{c^F}{\phi q(\phi)} = (1 - \eta) \left(\frac{-c^F - c^D + \theta m(\theta) p^N}{r + \delta + \theta m(\theta)} - k \right). \tag{19}$$

We now turn to the entry condition for buyers. Using the Bellman equations and the conditions in (12) gives

$$H = \frac{\varepsilon + sV^E}{r + s + \delta}, \tag{20}$$

$$V^E = \frac{-c^S + \theta m(\theta) \beta H}{r + \delta + \beta \theta m(\theta)}. \tag{21}$$

Solving the above system gives

$$H = \frac{r + \delta + \beta \theta m(\theta)}{(r + \delta + s + \beta \theta m(\theta))(r + \delta)} \left(\varepsilon - \frac{sc^S}{r + \delta + \beta \theta m(\theta)} \right), \tag{22}$$

$$V^E = -\frac{c^S}{r + \delta + \beta \theta m(\theta)} + \frac{\beta \theta m(\theta)}{(r + \delta + s + \beta \theta m(\theta))(r + \delta)} \left(\varepsilon - \frac{sc^S}{r + \delta + \beta \theta m(\theta)} \right). \tag{23}$$

Using the free entry condition $B = 0$ and combining the Bellman equation for buyers (7) with the Nash Bargaining rules in (12) gives the Buyer Entry (BE) condition

$$\frac{c^B(b)}{m(\theta)} = (1 - \beta)[\pi(H - V^E) + (1 - \pi)(H - k - V_1^N)]. \tag{24}$$

The BE condition captures that buyers enter the market until the expected cost of finding a house equals the buyer's expected surplus. Buyers incur flow costs $c^B(b)$ for an expected search duration $1/m(\theta)$. A buyer who finds a house is matched with an existing house with probability π and receives the surplus $S^{BE} = (1 - \beta)(H - V^E)$. With probability $1 - \pi$ she is matched with a new house instead, which gives a surplus $S^{BN} = (1 - \beta)(H - k - V_1^N)$. Using the Bellman equations and Nash Bargaining to derive S^{BE} and S^{BN} gives the following BE condition

$$\text{BE:} \quad \frac{c^B(b)}{m(\theta)} = (1 - \beta) \left[\frac{1}{\beta \theta m(\theta)} \left(\frac{r + \delta + q(\phi)}{q(\phi)} c^D + \rho \right) - \pi (V^E - \frac{c^D}{q(\phi)} - k) \right], \tag{25}$$

where $[1/(\beta\theta m(\theta))][(r+\delta+q(\phi))/q(\phi))c^D+\rho]$ corresponds to the surplus of a match with a new house S^N, and V^E is given by (23) and depends only on the housing market tightness and parameters.

Nash Bargaining combined with (13) and (14) gives the repayment (RR) condition,

$$\text{RR:}\ \ \phi = \frac{\eta}{1-\eta}\frac{c^F}{c^D}. \tag{26}$$

Similar to Wasmer and Weil (2004), free entry on both sides of the market and Nash Bargaining imply that the credit market tightness is determined by the ratio of the bargaining weights and the ratio of search costs. It is worth stressing that although the above condition determines the equilibrium credit market tightness, this condition is derived from bargaining, i.e. a price condition. Alternatively, it is possible to use Nash Bargaining and (15) to derive the equilibrium repayment, which is given by

$$\rho = (r+\delta)k + c^F + \frac{1-\eta}{\eta}(r+\delta+\theta m(\theta))\frac{c^D}{q(\phi)}. \tag{27}$$

The above equation is an alternative and equivalent expression in equilibrium to (26).[8]

In terms of housing prices, consider first the price of an existing houses. Nash bargaining (10) combined with the Bellman equations implies

$$p^E = \beta H + (1-\beta)V^E. \tag{28}$$

Substituting H and V^E from (22) and (23) gives the price condition for existing homes (PPE)

$$\text{PPE:}\ \ p^E = \frac{\beta}{r+\delta}\left[\frac{(r+\delta+\theta m(\theta))\varepsilon - \frac{r+\delta+\theta m(\theta)}{r+\delta+\beta\theta m(\theta)}sc^s}{r+\delta+s+\beta\theta m(\theta)}\right] - (1-\beta)\frac{c^S}{r+\delta+\beta\theta m(\theta)}. \tag{29}$$

Following a similar procedure gives the price condition for new houses (PPN)

$$\text{PPN:}\quad p^N = \frac{\beta}{r+\delta}\left\{\frac{(r+\delta+\beta\theta m(\theta))\varepsilon - sc^S}{r+\delta+s+\beta\theta m(\theta)}\right\} + (1-\beta)\left(k + \frac{c^D}{q(\phi)}\right). \tag{30}$$

Finally, the distribution π of existing houses is obtained from the laws of motion in the housing market. Let D denote the measure of developers, v_N and v_E the measure of vacancies of new and existing houses, and h the measure of homeowners. The following laws of motion

[8]Both (26) and (27) are derived using the Nash sharing rule (11). The difference between (26) and (27) is that (26) is derived using the free entry conditions to substitute for F_1 and V_1, whereas (27) uses F_1 from (15).

describe the dynamics of vacancies

$$\dot{v}_N = q(\phi)D - \theta m(\theta)v_N - \delta v_N, \tag{31}$$
$$\dot{v}_E = sh - \delta v_E - \theta m(\theta)v^E. \tag{32}$$

Equation (31) captures that the stock of new housing vacancies increases when developers find financing and build a new house, and is depleted when developers sell the new house or when the house receives a destruction shock. For existing houses, homeowners that experience a separation shock add to the stock of existing houses for sale. Similar to new housing, the stock of existing houses for sale depletes when the seller sells a house or the house is destroyed. The dynamics of the measure of homeowners h is governed by the following law of motion

$$\dot{h} = bm(\theta) - (s + \delta)h. \tag{33}$$

The flow into the stock of homeowners equals the number of buyers who find a house, whereas the flow out of this stock corresponds to homeowners who receive either a separation or destruction shock. In the steady state equilibrium $\dot{v}_N = \dot{v}_E = \dot{h}$, which implies the following steady state distribution

$$\pi = \frac{s\theta m(\theta)}{(s + \delta)(\delta + \theta m(\theta))}, \tag{34}$$
$$D = \frac{\theta m(\theta) + \delta}{q(\theta)}(1 - \pi)v, \tag{35}$$
$$h = \frac{bm(\theta)}{s + \delta}. \tag{36}$$

Definition 1. The equilibrium consists of a tuple $\{\phi, \theta, b, \rho, p^N, p^E, \pi, D, h, v^N, v^E, v\}$ that satisfies: (i) the HE condition (18); (ii) the CE condition (19); (iii) the BE condition (25); (iv) the RR condition (26); (v) the repayment condition (27); (vi) the PPE condition (29); (vii) the PPN condition (30); $(viii)$ the steady state distributions (34), (35) and (36); (ix) $v^E = sh/(\delta + \theta m(\theta))$; (x) $\theta = b/v$; (xi) $v = v^E + v^N$.

Note that the HE and CE conditions (18) and (19) imply the RR condition (26), so effectively the above definition corresponds to 11 equations in 11 unknowns. As in Wasmer and Weil (2004), the RR condition simply stresses the fact that the intersection between the CE and HE conditions happens at exactly $\phi = [\eta/(1 - \eta)](c^F/c^D)$.

Figure 1 describes the equilibrium graphically. The first panel depicts the HE and CE conditions from (18) and (19). To gain some intuition, hold p^N constant. An increase in housing market tightness θ makes it easier for sellers to sell houses. This induces entry of developers in the credit market and raises the credit market tightness ϕ. Since the price of

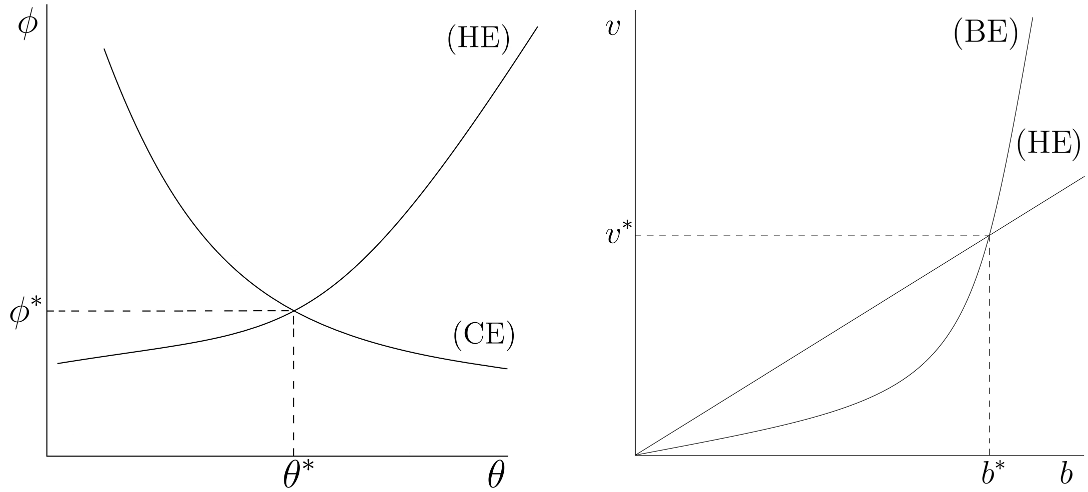

Figure 1: Equilibrium

new houses p^N is increasing in the housing market tightness, the same intuition follows when the price p^N is given by the PPN condition (30)—an increase in θ further raises prices and makes developers' entry more profitable. The CE curve is decreasing for a similar reason. The surplus of a match in the credit market increases with a rise in housing market tightness because developers can find a buyer more easily. As a result, more financiers enter the market and credit market tightness ϕ drops. The second panel depicts the Beveridge curve in the housing market from the BE condition (25). As in Gabrovski and Ortego-Marti (2019), more buyers enter the market when there is an increase in houses for sale because they are matched with houses at a faster rate, so the curve is upward sloping. The equilibrium measure of buyers and vacancies is given by the equilibrium market tightness (from the first panel) and the Beveridge curve. It is easy to verify that the equilibrium exists and is unique.

4 The quantitative effects of construction financing frictions

Our paper explores a novel channel that links credit frictions to the housing market through the liquidity constraints faced by real estate developers. In the current section we study the quantitative importance of this channel. To this end, we decompose the relative contribution of housing and credit market shocks to the observed housing market recovery in the U.S. during the 2012–2019 period. We focus on four data series that are central to the housing market and real estate development: (*i*) prices, (*ii*) time-to-sell, (*iii*) construction costs, and (*iv*) the fraction of existing home sales to total home sales. The shocks we consider are (*i*) a housing demand shock, captured by a change in the utility from housing ε, (*ii*) a housing supply shock, captured by a change in construction costs k, (iii) a friction shock, captured by a change in the search costs for developers c^D, and (iv) a housing tenure shock captured by a change in the separations rate s. It is common in the literature to consider both demand and supply shocks in the housing market to generate movements in prices and time-to-sell (Diaz and Jerez, 2013; Gabrovski and Ortego-Marti, 2021a; Head *et al.*, 2014; Ngai and Sheedy, 2020; Novy-Marx, 2009). We also consider both demand and supply shocks in the housing market. However, because of the credit frictions channel, the cost of creating a vacancy in the housing market has two components: a pure construction cost and a liquidity/search cost. The construction cost shock k generates movements in construction whereas our friction cost shock c^D generates movements in time-to-sell, i.e. the liquidity on the market. In addition, we consider a separation shock to match the observed change in the fraction of existing to total home sales. This is important because the supply of both new and existing houses determine the distribution of housing across new and existing homes.

As an overview of the results, our decomposition finds that the magnitude of the construction shock is about a third that of the friction shock in percentage terms, i.e. 39% and 116% respectively. In terms of the impact on the costs to create and maintain a vacancy, the total costs increased by about one half, but the share of the construction cost and the costs covered by the real estate developer remained constant at about 28% and 72%. We also gauge the model's ability to reproduce the observed decline in the vacancy rate and increase in housing construction. We find that the model over-predicts the observed vacancy rate decline only by about 10pp and is able to explain almost all of the observed increase in construction. These results suggest that our shocks capture well the change in liquidity that took place in the market during the 2012–2019 period. In a counterfactual exercise, we shut the financial shock. Absent any credit market disturbances, the model predicts that construction more than triples due to the relatively lower construction costs. This causes the vacancy rate to increase by about two thirds and the time-to-sell to double. In addition, the absence of credit shocks implies that prices increase only by 23% which is about half the increase observed in the data. In other words, the financial shocks explain about half of the empirically observed price increase.

4.1 Calibration

We calibrate the model at quarterly frequency. Our numerical exercise aims to explain the dynamics of the housing market recovery, so we focus on the 2012:1–2019:4 period. The discount rate is set to $r = 0.0086$ to match an annual real interest rate of 3.5%. Following the evidence in Van Nieuwerburgh and Weill (2010) we calibrate $\delta = 0.004$ to match a 1.6% annual housing depreciation rate. As in Diaz and Jerez (2013), we target an average of 9 years tenure in a home, so the separation rate s is set to 0.0238. The matching function elasticity for the housing market, α, is set to 0.16 following the evidence in Genesove and Han (2012). The corresponding elasticity of the credit market matching function is set to one half. We also set the bargaining powers in both markets to one half for symmetry. Lastly, we normalize $\varepsilon = 1$ and $\bar{c} = 0.1$.

The rest of the parameters $\{\mu,\ \mu_f,\ c^F,\ c^D,\ k,\ c^S,\ \gamma\}$ are calibrated to match seven data moments. Our exercise is focused on the trend of the recovery that took place in the U.S. economy. Accordingly, we set the time to sell in calibrated 2012:1 equilibrium to 1.4027 quarters, which is our estimate of the trend-fitted of the U.S. housing market time-to-sell for the first quarter of 2012.[9] Next, we follow the evidence in Genesove and Han (2012) and set the time-to-buy equal to the time-to-sell. The average search cost for the buyer are calibrated to 8% of the average purchase prices, following Ghent (2012) and the average costs for the seller are set to 2% which is close to the 2.28% that Gabrovski and Ortego-Marti (2019) have in their economy. To calibrate c^F we employ the strategy in Gabrovski and Ortego-Marti (2021a) and interpret c^F as liquidity costs, so we choose a c^F that matches the average spread between the yield on Moody's Seasoned Aaa Corporate Bond and the yield on 10-year constant maturity Treasury bonds for the period 2012:1 — 2019:4, which is 1.8617%. Next, we use data on the debt to equity ratio for real estate developer firms to calibrate the construction costs in the model, k.[10] Lastly, we pick $\gamma = 1.0512$ so that the model-implied movement in sales from our numerical exercise matches the movement in the data. Table 1 summarizes our calibrated parameter values.

4.2 Results

Having calibrated our model, we first note that the vacancy rate and the fraction of existing to total home sales in our equilibrium are 3.75% and 85.12% respectively. Their data counterparts are 2.2% and 92.79%. Thus, we can conclude that our calibrated model does a reasonably good job of replicating the U.S. economy. Next, we turn to our numerical exercise. Our main goal is to understand the dynamics of the housing market recovery following the 2006 crash and to decompose the observed patterns into underlying shocks. The period of interest is 2012:1 until 2019:4. We begin at 2012 because this appears to be the time around which housing construction began its recovery off the bottom. We end our period of interest in 2019 so as to not capture any of the effects of the COVID-19 pandemic. The dynamics of the housing market for that period are characterized by (i) an increase in housing prices, (ii) an increase in construction costs, (iii) a decrease in the time-to-sell, (iv) a decrease in the fraction of houses for sale that are existing homes, (v) an increase in sales, (vi) an increase in construction, and

[9]To be explicit, for information on the time-to-sell we use the Median Number of Months on Sales Market for Newly Completed Homes reported by the U.S. Census Bureau.

[10]The data on the market debt-to-equity ratio adjusted for leases, reported by Aswath Damodaran, can be found at `http://people.stern.nyu.edu/adamodar/New_Home_Page/dataarchived.html`.

(*vii*) a decrease in the vacancy rate.[11] Construction costs include not only the physical materials that go into a building, but also the labor costs, land value, land use regulations, permitting costs and planning costs among others. Thus, our finding rising construction costs is consistent with the increase in wages and salaries of workers in the construction sector and the increase in the cost of construction materials.[12] Moreover, there is abundant empirical evidence that land use regulations have increased significantly over the years (Ganong and Shoag, 2017; Glaeser and Ward, 2009). As Glaeser and Ward (2009) point out, "*increasingly stringent land use regulations have made it more and more difficult for developers to build*". Similarly, land values have also increased significantly over time.

We are interested in the trend of the recovery, and want to abstract away from any changes due to cyclicality and seasonality, so we regress each of the seven series on a constant and a linear time trend. We then obtain the fitted values and take the percentage difference between the first and the last fitted observation as our estimate for the magnitude of the trend changes over the period. Table 2 summarizes our findings. We see that prices increased by about 45% and construction costs by 39%, whereas construction saw a larger increase of about 67%. Sales increased by only 22% and the time-to-sell and the vacancy rate decreased by 30% and 34% respectively. At the same time the fraction of existing to total home sales in the data decreased by 4.6%. Together these numbers depict the following picture: higher construction costs lead to an increase in prices, but this was met with a simultaneous increase in the demand for housing that lead to more buyers in the market and subsequently lower vacancy rates and time-to-sell. At the same time, higher construction rates had a compositional effect which lead to a higher fraction of sales coming from new construction.

We decompose the observed stylized changes in house prices, time-to-sell, construction costs and the fraction of existing to total home sales into four components: a housing demand shock captured by a change in ε, a housing supply shock captured by a change in k, a financial shock captured by a change in c^D, and a separation shock captured by a change in s. We focus only on these four series to identify our shocks because: (i) they allows us to uniquely identify the shocks, and (ii) these four series are tightly linked to the supply and demand on the housing

[11] The series we use for house prices is the Case-Shiller seasonally adjusted National Home Price Index deflated by CPI less shelter. For construction costs we use the price index for Residential Structures Single Family taken from NIPA Table 5.3.4. Our series for existing home sales comes from the National Association of Realtors, whereas the series for new home sales is from the New Residential Sales release of the U.S. Census Bureau. Our series for construction is the New Privately-Owned Housing Units Started series from the New Residential Construction release of the U.S. Census Bureau. Lastly, our series for the vacancy rate is the Homeowner Vacancy Rate in the United States series from the Housing Vacancies and Homeownership release of the U.S. Census Bureau.

[12] For evidence on the increase in wages of construction workers see the Employment Cost Index for Wages and Salaries for Private Industry Workers in Construction released by the U.S. Bureau of Labor Statistics. For evidence on increasing costs of construction materials see the series Producer Price Index by Commodity: Special Indexes: Construction Materials released by the U.S. Bureau of Labor Statistics.

market. After we identify the shocks, we calculate the implied 2019 equilibrium in our model and compare the changes in construction and the vacancy rate to these in the data so as to gauge the ability of our shocks to explain the dynamics of untargeted moments.

Tables 3 and 4 present our findings. First, we see that the model implies the underlying utility households derive from housing increased by about one third. Second, construction costs in our model are captured by k, so the cost of construction increased by the exact same amount as its empirical counterpart. Third, the model implies that the frictional search cost for developers on the credit market more than doubled. This is because we observe a decrease in time-to-sell so the model has to reproduce a relatively larger response in buyers than in vacancies. Fourth, our analysis suggests that households changed their moving behavior by reducing the magnitude of the separations shock by about a quarter. This is implied by the relative decrease in the fraction of existing homes to total homes for sale in the market. Turning our attention to non-targeted moments, the model does a reasonably good job at replicating the magnitude of the drop in the vacancy rate and the increase in construction. This gives us confidence that our model and our decomposition are capturing the dynamics of the U.S. housing market during the recovery period well.

We now turn our attention to the decomposition part of our numerical examination. We conduct two exercises. First, we investigate the quantitative properties of our novel mechanism by analyzing the implied vacancy creation costs: how they changed over time and how their components changed as well. Next, we conduct two counter-factual exercises and ask what the change in prices, time-to-sell, construction, and the vacancy rate would be absent: (i) the financial shock; (ii) the shock to the separation rate. Table 5 summarizes our findings on the vacancy costs. We see that the total cost of creating and maintaining a vacancy in the housing market increased by about one half. Moreover, the contribution of the construction and the financial costs remained unchanged, as evidenced by the constant share of construction costs to total costs. In addition, the share of the cost covered by the developer also remained constant at about 72%.

Table 6 depicts our counter-factual exercises. First, when the level of search costs c^D is kept constant at its initial level, i.e. absent the financial shock, we see that construction more than triples. This is because the total costs of creating a vacancy are now relatively lower. This relatively larger increase in construction leads to about two thirds increase in the vacancy rate and a more than doubling of the time-to-sell indicating that the market would have featured a lot more houses for sale relative to buyers. Together the relative abundance of houses and lower construction costs imply that prices would have increased by only about a quarter. This is only about a half of the actual increase in prices observed in the data. Thus, we conclude that the financial shock in our model accounts for about 50% of the observed house prices increases during the 2012 — 2019 period.

In our second counter-factual exercise, when we keep the separation rate fixed at its initial level, we see that prices, time-to-sell, and the vacancy rate are almost unchanged from their data counterparts. Thus, we conclude that these variables are tightly linked to vacancy creation costs and the conditions on the credit market, but not impacted as much by the length of housing tenure. Total amount of construction, however, is heavily impacted and is in fact 4.5% lower in our counter-factual scenario relative to the initial period. Thus, construction and entry of developers into the market is strongly linked to the frequency with which households move homes. The intuition behind this is the following. Absent the change in the separation rate, s, households move homes more often. Because of this, more existing homes are put for sale on the market which serves to increase the amount of vacancies. Thus, developers have less of an incentive to build new homes and, as a result, do not enter the market as much as they do in the data. Moreover, the relatively little change in prices, time-to-sell, and the vacancy rate imply that the increase in existing home vacancies is almost entirely offset by a decrease in new home creation, so that the total number of vacancies on the market is barely changed.

5 Conclusion

In this paper we build a search and matching model of the housing market to understand the effect of credit frictions faced by developers on the housing market. The key ingredients in the model are search and matching frictions in the housing and credit markets, bargaining over prices and free entry of buyers, developers and financiers. Our model proposes a novel channel through which credit frictions faced by developers affect the housing market. We quantify the size of this credit channel by calibrating the model to the US economy and decomposing the relative contribution of housing and credit market shocks to the observed housing market recovery in the U.S. during the 2012–2019 period. The model closely matches a number of targeted and non-targeted moments, giving us confidence that our mechanism captures well the housing market recovery during the 2012–2019 period. Through a series of counterfactuals we find that the credit channel had a large impact on the housing market, especially liquidity, and accounts for about half of the increase in prices during the 2012–2019 housing recovery.

This paper assumes that separations occur exogenously, and uses data on the distribution of sales across new and existing houses to calibrate shocks to the separation rate. Although we show that the separation shock almost uniquely affects the distribution of sales and does not drive our results (the effect on prices and time-to-sell and the vacancy rate is negligeable), it would be interesting to understand the determinants of house separations. In current work in progress (Gabrovski and Ortego-Marti, 2021c), we study endogenous separations in a search matching model of the housing with endogenous entry of buyers to understand the role of endogenous separations in housing market dynamics.

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Preferences/Technology	Parameter	Value	Source/Target
Discount rate	r	0.0086	Annual interest rate= 3.5%
Utility	ε	1	Normalization
Elasticity of Matching Function	α	0.16	Genesove and Han (2012)
Elasticity of Matching Function	α_f	0.5	TTB=TTS
Destruction rate	δ	0.004	Van Nieuwerburgh and Weill (2010)
Separation Rate	s	0.0238	Tenure= 9 years
Efficiency of Matching Function	μ	0.7129	TTS= 1.4027 quarters
Efficiency of Matching Function	μ_f	0.0318	
Seller cost	c^S	0.959	Average seller cost= 2% of price
Developer cost	c^D	3.4185	Average buyer cost= 8% of price
Financier cost	c^F	0.0648	Moody's AAA-Treasury Bill spread
Bargaining power	β	0.5	
Bargaining power	η	0.5	
Construction cost	k	14.019	Debt-to-equity ratio 94.7%
Buyer cost scale parameter	$\bar{c}$	0.1	Normalization
Buyer cost elasticity parameter	γ	1.05	21.17% increase in sales from 2012:1 to 2019:4

Table 1: Calibration

Series	Percentage Change
Prices	44.82%
Time to Sell	−30.13%
Construction Costs	39.22%
Sales	22.17%
Construction	66.76%
Vacancy Rate	−34.35%
Existing to Total Home Sales	−4.6%

Table 2: Empirical Recovery Facts

Variable	Percentage Change	Target Series Percentage Change
ε	35%	Prices
k	39.22%	Construction costs
c^D	115.63%	Time-to-sell
s	-25.77%	Existing to Total Home Sales

Table 3: Size of Calibrated Shocks

Moment	Percentage Change in Data	Percent Change in Model
Construction	66.76%	54.06%
Vacancy Rate	-34.35%	-44.6%

Table 4: Untargetted Data Moments

	Total Costs	Percent Construction Cost	Percent Developer Cost
Initial Period	48.51	28.9%	72.16%
End Period	70.28	27.77%	72.96%

Table 5: Vacancy Costs

No Change in Frictions Shock, c_D				
Variable	Price	Time-to-Sell	Construction	Vacancy Rate
Counter-factual Change	23.03%	124.5%	244.06%	70.2%
No Change in Separation Shock, s				
Variable	Price	Time-to-Sell	Construction	Vacancy Rate
Counter-factual Change	44.88%	-36%	-4.52%	-35.12%

Note.- Table 6 reports the counterfactual changes in house prices, time-to-sell, construction, and the vacancy rate absent the friction shock and the separation shock.

Table 6: Shock Decomposition