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.

JEL Classification: E2, E32, E44, G21, R21, R31.
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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%. Moreover, developers rely heavily on external financing for their construction and development projects. For example, during 2012 — 2019 more than 50% of respondents in the NAHB Survey on Acquisition, Development & Construction Financing reported seeking new loans for single-family construction projects.[1] 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, we study 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, 2021; Petrosky-Nadeau and Wasmer, 2017; Wasmer and Weil, 2004).[2] 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

[1] See the 2024Q1 Survey on Acquisition, Development & Construction Financing available on the NAHB website and the historical information contained therein.

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

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 financiers and developers, and influences the terms of trade in the credit market.

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. Empirically, the recovery featured the following stylized facts: (i) prices increased by 45%; (ii) time-to-sell decreased by 30%; (iii) sales increased by 21%; (iv) construction increased by 67%; (v) the vacancy rate decreased by 34%; (vi) the fraction of existing to new home sales decreased by 5%; (vii) the amount of construction and development loans outstanding increased by 90%.[3] Construction of new homes, in particular, 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.

The calibrated model is able to exactly match a number of targeted moments, including the observed increase in prices, the amount of construction and development loans outstanding, and the fraction of new home sales, as well as the observed decline in time-to-sell. Importantly, the model also matches well three key non-targeted moments: the observed decline in the vacancy rate and the increase in housing construction and sales. These results give us confidence that our mechanism captures well the housing market recovery during the 2012–2019 period. Overall, our results are 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, and longer housing tenure, 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 and housing market frictions. We find that the total vacancy cost increased by about 50% during the period. Yet, the fraction of the cost due to frictions decreased from 70% to 63%. Moreover, the fraction of the financial cost borne by the developer (vs. the financier) also decreased from 71% to 64%. Delving deeper into the credit channel we find that the credit search costs for developers per unit of time increased by 81%,

[3]For a detailed description on how we obtain the stylized facts, see section 4.1.

consistent with the empirically observed tightening of lending standards. At the same time, the higher demand for homes and construction credit lead to an increase in available loans which reduced the average time it takes to find a loan by about a quarter. This is also consistent with the observed greater availability of loans in 2019 as compared to 2012.[4] Overall, the two effects lead to an increase in the average costs to obtain a credit line of 35%.

Motivated by these findings, we simulate a series of counter-factuals that shed greater light on the importance of the credit channel for the recovery. First, we shut down the shock to the credit market to quantify the role of credit frictions in accounting for the stylized facts during the housing market recovery. Absent the shock to the credit market, construction more than doubles due to lower total costs of creating a vacancy. The increase in construction raises the vacancy rate by about a fifth, but also leads to about 50% longer 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. Although there was some increase in buyers as evidenced by the 80% increase in sales absent the shock. Interestingly, and perhaps intuitively, in the absence of the credit shock 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 the credit shock.[5] Overall, our results suggest that credit frictions had large impact on liquidity, construction and vacancies, and that they can account for about half of the rise in prices during the housing market recovery 2012-2019. We conduct two additional counter-factual exercises where we keep fixed, one at a time, the seller's search costs on the housing market and the home separation rate to their initial 2012 level. These parameters are adjacent to the credit channel in our environment because they affect the total vacancy costs and the composition of houses for sale, i.e. the amount of existing houses for sale new construction has to compete with. We find that these two were important for the observed changes in market liquidity but not for prices: absent these shocks, prices respond about the same as they do in the data.

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; Arefeva *et al.*, 2024; Burnside *et al.*, 2016; Diaz and Jerez, 2013; Gabrovski and Ortego-Marti, 2019, 2021, 2022; Gabrovski *et al.*, 2024; 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.*,

[4]For a detailed discussion see section 4.3 of this paper.

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

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.[6]

Among the papers mentioned above studying models of the housing market with search frictions, only Gabrovski and Ortego-Marti (2019, 2021, 2022), Gabrovski *et al.* (2024), 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 (2021) 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.

Finally, our paper is broadly related to the seminal work in Wasmer and Weil (2004) (see also Petrosky-Nadeau and Wasmer (2017) and Gabrovski *et al.* (2023)). As in Gabrovski and Ortego-Marti (2021), 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 markets. After describing the environment, we characterize the equilibrium. Next, we derive the stylized facts of the 2012

[6]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).

— 2019 market recovery and 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.

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 (2021). 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.[7] 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 *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

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

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 (2021), Petrosky-Nadeau and Wasmer (2017), Gabrovski *et al.* (2023), 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.[8] 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. Ambrose and Peek (2008) find large and significant effects of credit access for home construction.

The assumption of search frictions in the credit market is further supported by several findings in the finance literature. First, a large literature finds that relationship lending plays a very important role in banks' lending decisions (Agarwal *et al.*, 2018; Agarwal and Hauswald, 2021; Berger and Udell, 1995; Petersen and Rajan, 1994, 1995, 2002). This literature finds empirical evidence that banks rely significantly on *soft* information to make lending decisions (Agarwal *et al.*, 2018; Agarwal and Hauswald, 2021), where soft information refers to information that is hard to capture in written documentation—as opposed to *hard* information such a a credit score. Because this information is difficult to communicate and/or store, banks must collect it by interacting and forming a relationship with firms, which requires banks to locate near firms seeking funding, and requires costly and time consuming search efforts from both the lender and the firm seeking funding before a loan is approved and accepted. The empirical findings

[8]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.

from this literature show that distance between lenders and borrowing firms is an important factor for the availability of credit and is a good predictor of credit quality. Relationship lending seems a particularly important aspect of lending in construction, given that construction projects are quite heterogeneous and require local knowledge of the local housing market and policies. In this context, it becomes very valuable for banks to gather soft information on the borrowing developer and project to assess the suitability and risk of a potential loan.

In addition, a large literature finds evidence of loan prospecting by banks. Loan prospecting refers to banks' activity that requires loan officers to sell the bank's loan products. The literature finds that banks engage significantly in loan prospecting and provide significant incentives to loan officers to actively promote certain loans, and reward loan officers for reaching certain loan volumes (Agarwal *et al.*, 2018; Agarwal and Ben-David, 2018; Heider and Inderst, 2012).[9] Agarwal and Ben-David (2018) and Agarwal *et al.* (2018) describe the loan approval process in detail, which is as follows. Firms start by inquiring with a loan officer about a funding opportunity. Usually the loan officer then encourages the firm to submit an application, along with any required supporting information. The loan officer then processes the application and conducts an in-depth interview to understand the reasons behind the loan request and to gather soft information on the client/project. The loan officer then determines an internal risk-rating score. Combining the internal risk score with any available hard information, the loan officer can adjust the bank's internal score. Together with the branch manager, the loan officer makes the decision on whether to approve the loan and its terms. See Agarwal and Ben-David (2018), section 2.1. for a detailed description of the loan approval process.

Importantly for our motivation of search frictions in the credit market, Agarwal and Ben-David (2018) find that 43% of loan applications are approved, and the rest are rejected. Out of the 43% of applications approved, 12% were rejected/withdrawn by the firm seeking the loan after being approved. Conditional on being approved, it takes on average 1.3 months for a loan application to be approved. When rejected, firms continue to seek approval at other banks, and banks continue to search for clients for their loan products Agarwal *et al.* (2024).[10] Our

[9]As Heider and Inderst (2012) point out, the U.S. Department of Labor description of a loan officer is as follows: *"In many instances, loan officers act as salespeople. Commercial loan officers, for example, contact firms to determine their needs for loans. If a firm is seeking new funds, the loan officer will try to persuade the company to obtain the loan from his or her institution. [...] The form of compensation for loan officers varies. Most are paid a commission that is based on the number of loans they originate. In this way, commissions are used to motivate loan officer to bring in more loans. Some institutions pay only salaries, while others pay their loan officers a salary plus a commission or bonus based on the number of loans originated."*

[10]Although this evidence is provided for firm loans in general, there is a large amount of empirical evidence that developers face similar financing needs and issues. The Survey on Acquisition, Development & Construction Financing from the National Association of Home Builders reports that 45% of developers sought new loans in 2024. Of those developers not seeking a loan, over 50% state that it is because they are not engaged in a construction project. The average length of the loan is about 15 months, which a significantly larger interest rate compared to mortgages of around 6% (the effective interest rate is even higher, around 9%). In 2012, 75% of respondents reported that the availability of loans is "about the same" or "worse". Of those who responded

environment with search frictions captures this type of loan seeking process and frictions that both firms and borrowers face, and the approval process, with its inherent probability of not securing a loan or not securing a firm willing to borrow. In addition, there is evidence of banks' entry decisions in certain credit markets, such as developer loans or mortgages. As den Haan *et al.* (2003) bank's equity and previous loan performances affect the quantity of loans offered and issued by banks. Similarly, Ambrose and Peek (2008) show that credit markets are crucial for the market positions of developers. They find that during the 1988 to 1993 period, banks with a deteriorated financial condition reduced their lending to the construction industry. In our environment banks' participation costs (which capture among others opportunity costs of alternative investment or costs to raise equity) determines banks entry or the banks "desire" to enter a particular loan market. Together with borrowers' search costs and their entry decision, the bank's entry decision determines the credit market tightness.

Finally, Cipollone and Giordani (2019a,b) estimate the matching function between entrepreneurs and financiers in the business angels and venture capital segments. These studies find that the matching function satisfies the common assumptions in search and matching models, and that we adopt in our environment. In particular, they show that the matching function satisfies constant returns to scale, that returns are diminishing in each input, and importantly that there are thick-market effects, i.e. the marginal effect of an increase in the number of entrepreneurs is increasing in the number of financiers. They find that Cobb-Douglas is a good approximation for the matching function, with a parameter of around a half.

Our environment with search frictions is trying to capture the types of frictions that borrowing firms and banks face described above. Whereas our environment focuses on the credit frictions from costly search, entry in the credit market and bargaining over prices, it is worth stressing that these frictions are complementary to frictions related to collateral constraints and fluctuations in the value of collateral in the spirit of Kiyotaki and Moore (1997). In reality, the credit market is clearly subject to both sources of frictions. A full comparison between the effects of both types of credit frictions is, however, beyond the scope of this paper and left for future research.

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, 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

"worse", 43% cite "not making new loans" and 38% "refusing to make relationship loans" as the reasons.

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. Implicitly, this assumes that developers have enough funds to cover the fee ρ, but need to seek financing for the construction cost k.[11] Gabrovski and Ortego-Marti (2021) make a similar assumption for mortgages, households have enough funds to cover a down payment, but must secure financing for the remainder of the house price. 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), or the costs of raising equity in the spirit of den Haan *et al.* (2003).[12]

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, 2021), 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

[11] This assumption is consistent with the observed interest rate payment structures for development loans, see the Survey on Acquisition, Development & Construction Financing from the National Association of Home Builders.

[12] See Gabrovski and Ortego-Marti (2021) 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

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

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

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. These search costs are different than the ones from the earlier stage. Whereas during the search for financing the developer must prepare documents and maintain construction sites ready for inspection for financiers, during this stage the developer searchers for home buyers and so pays the search costs c^S. These are costs associated with realtor fees and home transaction fees. 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 $H - p^N - B$.[13]

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 (2021) 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.

[13]We assume that buyers search for both types of houses, since they are identical and both yield a positive surplus. A question worth pursuing is the study of an environment in which new and old houses are different, and in which buyers direct their search towards one type of housing. Similarly, another interesting extension would allow developers to adjust the quality of new housing in response to credit conditions. Although both extensions are worth pursuing, they are beyond the scope of this paper and left for future research.

The first order conditions to the above two bargaining problems give the following sharing rules[14]

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

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

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

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

[14]It is worth pointing out that when calculating the Nash-maximand the transition rates do not show up because the house price and repayment they involve refers to the threat point, which the party renegotiates later with a new bargaining partner, but not in the current match. This is also the case in most labor-search models, where wages are negotiated using Nash bargaining. Nonetheless, after we have derived the rules in (10) and (11) and substitute these into the equilibrium expressions for F_1, V_1, H, V^E the transition rates do appear since they affect the size of the surplus. In particular, the surplus of the match between the developer and the bank depends on the house-selling rate $\theta m(\theta)$, as it dictates when the developer will be able to sell the house and repay the bank; the surplus between the buyer and seller also depends on this rate because when the buyer purchases a home, she may experience a separation shock which will cause her to place the home for sale and derive the value V^E for it, which depends on the time-to-sell.

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

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

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

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 (12), implies the following HE and CE conditions

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

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

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

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

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

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 $S^{BN} = (1-\beta)(H - k - V_1^N)$.

Combining (3), (20), (22), and (23), together with $p^N - k - V_1 = \beta(H - k - V_1)$, yields the following surpluses for a match with an existing and a new house

$$H - V^E = \frac{\varepsilon + c^S}{r+\delta+s+\beta\theta m(\theta)}, \tag{25}$$

$$H - k - V_1 = \frac{\varepsilon + c^S}{r+\delta+s+\beta\theta m(\theta)} + \frac{\rho - (r+\delta)k}{r+\delta+\beta\theta m(\theta)}. \tag{26}$$

Both match surpluses include the flow ε that the buyer derives from owning a house, and the flow costs c^S that the seller saves when forming a match. In addition, the surplus of a match with a new house takes into account that developers save the financing fee ρ net of the user cost $(r+\delta)k$ when forming a match. The above surpluses equal the present discounted value of all these flows, using the appropriate effective discount rate in each case.

Substituting the above expressions into (24) gives the following BE condition

$$\text{BE:} \quad \frac{c^B(b)}{m(\theta)} = (1-\beta)\left[\frac{\varepsilon + c^S}{r+\delta+s+\beta\theta m(\theta)} + (1-\pi)\frac{\rho - (r+\delta)k}{r+\delta+\beta\theta m(\theta)}\right]. \tag{27}$$

Intuitively, the BE condition captures that regardless of the type of house, the surplus in any match includes the present discounted value of the utility flows from owning a house ε and the seller's flow search costs c^S, all discounted using the effective discount rate. In addition, in meetings with new houses, which happen with probability $1-\pi$, the surplus also includes the present discounted value of the financing fees ρ net of the user costs $(r+\delta)k$, also discounted with the relevant effective discount rate. In a sense, when a buyer meets a new house they meet with a more motivated seller. These meetings carry a larger surplus, because the developer saves the net financing fee when a match is formed, similar to Arefeva *et al.* (2024).

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

$$\text{RR:} \;\; \phi = \frac{\eta}{1-\eta}\frac{c^F}{c^D}. \tag{28}$$

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

$$\rho = (r+\delta)k + c^F + \frac{1-\eta}{\eta}(r+\delta+\theta m(\theta))\frac{c^D}{q(\phi)}. \tag{29}$$

The above equation is an alternative and equivalent expression in equilibrium to (28).[15]

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

$$p^E = \beta H + (1-\beta)V^E. \tag{30}$$

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

$$\text{PPE:} \;\; p^E = \frac{\beta}{r+\delta}\left[\frac{(r+\delta+\theta m(\theta))\varepsilon - \frac{r+\delta+\theta m(\theta)}{r+\delta+\beta\theta m(\theta)} s c^s}{r+\delta+s+\beta\theta m(\theta)}\right] - (1-\beta)\frac{c^S}{r+\delta+\beta\theta m(\theta)}. \tag{31}$$

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

$$\text{PPN:} \quad p^N = \frac{\beta}{r+\delta}\left\{\frac{(r+\delta+\beta\theta m(\theta))\varepsilon - s c^S}{r+\delta+s+\beta\theta m(\theta)}\right\} + (1-\beta)\left(k + \frac{c^D}{q(\phi)}\right). \tag{32}$$

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

[15] Both (28) and (29) are derived using the Nash sharing rule (11). The difference between (28) and (29) is that (28) is derived using the free entry conditions to substitute for F_1 and V_1, whereas (29) uses F_1 from (15).

describe the dynamics of vacancies

$$\dot{v}_N = q(\phi)D - \theta m(\theta)v_N - \delta v_N, \tag{33}$$

$$\dot{v}_E = sh - \delta v_E - \theta m(\theta)v^E. \tag{34}$$

Equation (33) 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

$$\dot{h} = bm(\theta) - (s+\delta)h. \tag{35}$$

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

$$\pi = \frac{s\theta m(\theta)}{(s+\delta)(\delta + \theta m(\theta))}, \tag{36}$$

$$D = \frac{\theta m(\theta) + \delta}{q(\theta)}(1-\pi)v, \tag{37}$$

$$h = \frac{bm(\theta)}{s+\delta}. \tag{38}$$

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 (27); (iv) the RR condition (28); (v) the repayment condition (29); (vi) the PPE condition (31); (vii) the PPN condition (32); $(viii)$ the steady state distributions (36), (37) and (38); (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 (28), 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 $\phi = [\eta/(1-\eta)](c^F/c^D)$.

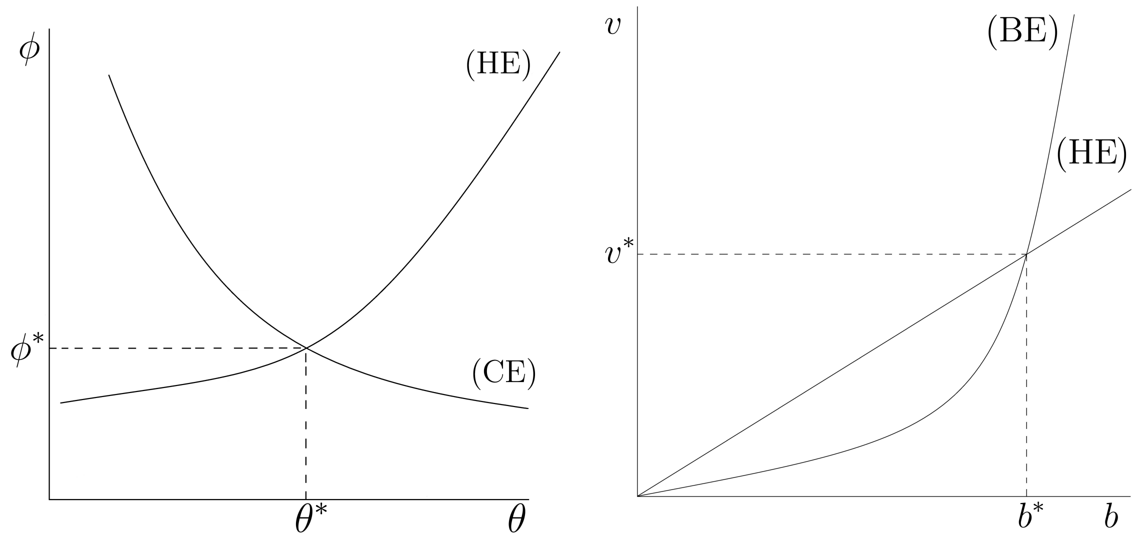
Figure 1 describes the equilibrium graphically. The first panel depicts the HE and CE conditions from (18) and (19). To gain some intuition, hold p^N constant. An increase in housing market tightness θ makes it easier for sellers to sell houses. This induces entry of developers in the credit market and raises the credit market tightness ϕ. Since the price of 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 (32)—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 (27). 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.

The equilibrium is in general inefficient because there is a participation externality in addition to the usual congestion/thick market externality, similar to Gabrovski and Ortego-Marti (2021). Without the endogenous entry of both buyers and sellers, the decentralized allocation is efficient under a Hosios-Mortensen-Pissarides condition (HMP) in both the credit market and housing market, as in Petrosky-Nadeau and Wasmer (2017) and Wasmer and Weil (2004). However, Gabrovski and Ortego-Marti (2021) show that the equilibrium is inefficient in an environment without credit but with endogenous entry of sellers and buyers as in this paper, even if the HMP condition holds. Intuitively, when buyers decide whether to enter the market, they do not take into account that by entering they raise search costs for all buyers through the congestion in $c^B(b)$. An HMP condition in the credit market and housing market controls for the congestion/thick market externality, but the social planner requires an additional tool to adjust the entry of buyers to its efficient level—see Gabrovski and Ortego-Marti (2021) for a more detailed explanation and results. To the extent that credit market regulations can set the entry level to its efficient level, they may restore efficiency in the decentralized equilibrium.[16]

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 this section, we investigate the quantitative implications of this channel for prices and liquidity on the market. To this end,

[16] A full study of efficiency in our environment with frictions in both credit and housing markets, although very interesting, is beyond the scope of this paper. In particular, our paper does not answer whether the availability of loans and entry of banks is efficiency, or whether credit market regulations can restore the efficient allocation. This is without a doubt something that is worth pursuing, but that is left for future research. We are grateful to an anonymous referee for helpful comments and suggestions on this issue.



(a) Equilibrium market tightnesses θ^* and ϕ^* (b) Equilibrium buyers b^* and vacancies v^*

Note.- *Figure 1a depicts the house entry condition (HE) from (18) and the credit entry relationship (CE) from (19), which determine the equilibrium housing market tightness $\theta^* = b^*/v^*$ and credit market tightness $\phi^* = \mathcal{D}^*/\mathcal{F}^*$. The (HE) condition in figure 1b depicts the equilibrium ratio of buyers to sellers from figure 1a, which is a straight line with a slope proportional to the equilibrium tightness on the housing market. The (BE) curve is the graphical representation of the buyers entry condition (27). It shows that an increase in the ratio of housing vacancies to buyers makes it easier for buyers to find a house which incentivizes further entry for buyers. The (BE) curve is analogous to the Beveridge Curve in search models of the labor market and is upward sloping due to entry of buyers, developers, and financiers.*

Figure 1: Equilibrium in the housing market and credit markets

we calibrate the model to the U.S. economy and use the post 2007 market crash recovery as a laboratory. The recovery lasted from about 2012 until the onset of the COVID-19 pandemic in 2020 and features the following empirical regularities: prices, construction, sales, and the amount of construction and development loans outstanding all increased, whereas time-to-sell, the vacancy rate, and the fraction of existing to total home sales all decreased.

To capture these regularities, we allow for several key model parameters to adjust. In particular, we follow the existing literature on the housing market (Diaz and Jerez, 2013; Gabrovski and Ortego-Marti, 2021; Head *et al.*, 2014; Ngai and Sheedy, 2020; Novy-Marx, 2009) and use both demand and supply shocks to generate movement in prices and time-to-sell. The demand shock we consider is a change in the utility from housing, ε and the supply shock moves the construction cost, k. We capture the movements in the amount of loans outstanding for construction and development through a shock in c^D, the developer's construction cost. This is a key model parameter that governs how expensive it is to find credit in the model, so we dub this the "credit shock" and use it to study the quantitative importance of the credit channel in the model. To make sure it only captures financial frictions and not search frictions in the housing market, we also allow for c^S to adjust so as to capture the empirically observed stable (as a fraction of the price) realtor fees. Lastly, the importance of new housing creation for sales is captured with a shock in separations s, which dictates how often households switch homes.

The focus of our paper is on the trend behavior of the housing market, rather than on business cycle fluctuations. Hence, we focus our analysis on steady state elasticities similar to Gabrovski and Ortego-Marti (2021) and Ngai and Sheedy (2020). As Shimer (2005) points out, these elasticities give a good sense locally of the model response to an innovation. Moreover, the housing market appears to recover from shocks relatively quickly, so a steady state comparison is more appropriate than an analysis of impulse response functions to shocks, since our period of interest is 8 years.[17]

As an overview of the results, our decomposition finds that the utility of homeownership increased by about a third and construction costs almost doubled. The developer's search costs for financing, c^D, and the seller's search costs on the housing market, c^S, increased by 80% and 110%, whereas the rate of separations, s, decreased by about a quarter. In terms of the impact of the increases in construction and search costs on the total costs to create and maintain a vacancy, total costs increased by about 50%, the share of construction costs increased by about a third, and the share of costs covered by the developer decreased by about 10%. In a counterfactual exercise, we ask how would the housing market have looked in 2019 had the costs for developers, c^D remained at their 2012 level. The model predicts that construction more than doubles due to the relatively lower vacancy costs. This causes the vacancy rate to increase by about 20% and the time-to-sell to increase by a half. In addition, the prices would have increased only by 25% which is about half the increase observed in the data. In other words, the credit shock explains about half of the empirically observed house price increase. The shocks to search costs c^S and housing tenure (s) were important for liquidity, but do not explain much of the price movements.

4.1 Empirical recovery facts

Data. We begin by outlining the empirical recovery facts present in the data. To this end we collect information on several housing and credit market variables. The data on prices is the seasonally adjusted Case-Shiller U.S. National Home Price Index that we deflate using the Consumer Price Index for All Urban Consumers: All items less shelter (released by Standard & Poor's and the U.S. Bureau of Labor Statistics). For information on time-to-sell we use the data on Median Number of Months on 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. From the same release we extract data on new home sales: New

[17]For example, the average time-to-sell of newly created homes on the market prior to the 2006 crash was 4.9 months. 3 years later, at the peak of the crash (the forth quarter of 2009) it was 13.9 months and another 3 years later, it had recovered to its pre-crash levels. Similarly, prices took about 4 years to recover from the bottom to their pre-crash levels.

Series	Percentage Change
Prices	44.82%
Time-to-sell	−30.13%
Sales	21.17%
Construction	66.76%
Vacancy Rate	−34.35%
Existing to Total Home Sales	−4.6%
Construction and Development Loans	90.02%

Note.- *Table 1 summarizes the stylized facts of the 2012 — 2019 housing market recovery. The facts are obtained by regressing each of the series for (i) prices; (ii) time-to-sell; (iii) sales; (iv) construction; (v) the vacancy rate; (vi) the fraction of existing to total home sales; (vii) the amount of construction and development loans outstanding on a constant and a linear time trend. We then take the first (2012:1) and last (2019:4) fitted values and compute the percentage change for each series.*

Table 1: Stylized facts

One Family Houses Sold: United States. For data on existing home sales we turn to the National Association of Realtors' series Existing Home Sales. For information on construction we look at the New Privately-Owned Housing Units Started: Total Units reported in the New Residential Construction release by the U.S. Census Bureau and the U.S. Department of Housing and Urban Development. The data on vacancy rates is the Homeowner Vacancy Rate in the United States series from the Housing Vacancies and Homeownership release by the U.S. Census Bureau. Lastly, for information on the financial side of the market we use information on loans from the FDIC Quarterly Banking Profile made available by the Federal Deposit Insurance Corporation. In particular, we take the Balance Sheet: Total Assets: Loans Secured by Real Estate: Construction and Development series which we deflate using the Consumer Price Index for All Urban Consumers: All Items Less Shelter in U.S. City Average.

Stylized facts. We obtain the stylized facts in the following way. First, we gather the data for the 2012:1 — 2019:4 period and then regress each of the 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 of the magnitude of the trend changes over the period. These form our stylized facts summarized in Table 1.

The goal of our numerical exercise is to understand the dynamics of the market recovery following the 2006 crash. Thus, we begin at 2012 because this appears to be the time around which 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. Furthermore, our analysis is focused on the trend of the recovery, so we abstract away from any changes due to cyclicality and seasonality. Figure 2 visualizes the data and its fitted values. We can note that a linear time trend appears to capture the data movements quite well. An alternative approach to abstract away from short-term fluctuations is to obtain the percentage difference between the average values for 2012 and 2019. We present our findings following this approach in Appendix A. Qualitatively, the stylized facts remain the same although the change in loans under the alternative approach is only about 60%. The rest of the stylized facts are quantitatively similar.

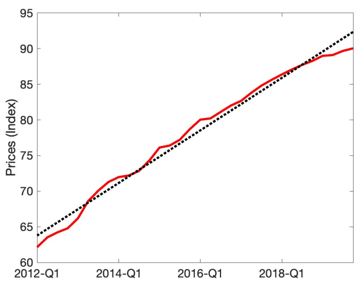
Turning to the stylized facts we see that prices and construction increased by about a half during the recovery period. At the same time loans almost doubled, whereas sales increased by about only a fifth. These were accompanied by about a third decrease in the time-to-sell and the vacancy rate. The fraction of existing to new home sales exhibited a downward trend but decreased only by about 5%. Taken together these facts paint the following picture. The market heated up leading to an increase in prices, a rise in construction, and an increase in sales. At the same time, there were fewer existing homes listed for sale, so the number of available vacancies decreased. This was associated with a lower congestion on the market and, hence, a lower time-to-sell. Lastly, the increase in construction was associated with an increase in the amount of construction and development loans outstanding. In the remainder of this section we conduct a numerical exercise to uncover the drivers behind the housing market dynamics and the importance of the credit channel for these dynamics in particular.

4.2 Calibration

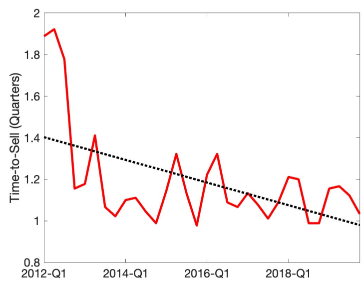
Next, we turn to the calibration strategy. Our numerical exercise aims to explain the dynamics of the housing market recovery, so we focus on the 2012:1–2019:4 period. The discount rate is set to $r = 0.0086$ to match an annual real interest rate of 3.5%. Following the evidence in Van Nieuwerburgh and 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, following Petrosky-Nadeau and Wasmer (2013) and Gabrovski *et al.* (2023). There is not much empirical evidence on the bargaining power in the housing market. Consequently, we set $\beta = 0.5$, following the approach in much of the existing literature (see, for example, Gabrovski and Ortego-Marti (2019), Ngai and Tenreyro (2014), Ngai and Sheedy (2020), Ngai and Sheedy (2024)). Furthermore, even papers which attempt to recover the bargaining power using aggregate data targets find it to be close to one half. For example, Gabrovski and Ortego-Marti (2021) finds $\beta = 0.5673$. We normalize $\varepsilon = 1$.[18]

The rest of the parameters $\{\mu,\ \mu_f,\ c^F,\ c^D,\ k,\ c^S,\ \eta,\ \gamma\}$ are calibrated to match eight data moments. We pick these moments because they are most important to match in our calibrated

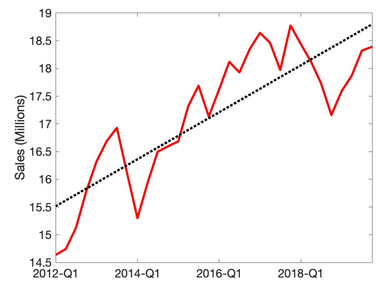
[18]In search models of the housing market, one can normalize ε to any positive value since all costs and prices are proportional to it. This is also standard in models of the labor market.



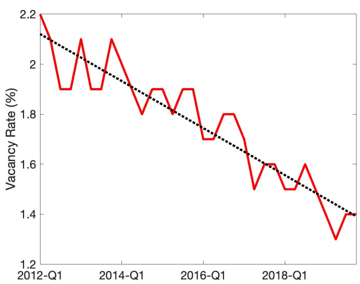
(a) Prices



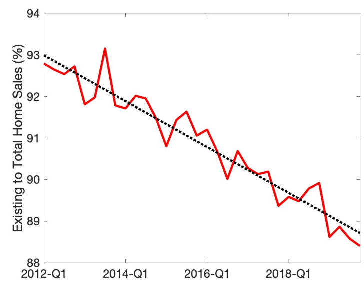
(b) Time-to-sell



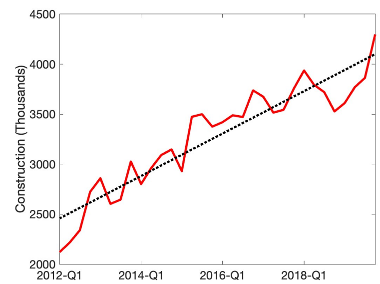
(c) Sales



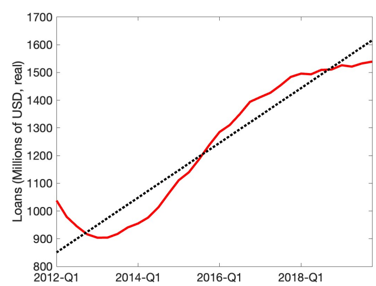
(d) Vacancy Rate



(e) Fraction of existing to new home sales



(f) Construction



(g) Construction and Development Loans Outstanding

Note.- *Figure 2 graphs the data (solid line) and fitted values (dotted line) for (i) prices (index, 2a); (ii) time-to-sell in quarters (2b); (iii) sales in millions of units (2c); (iv) vacancy rate in percentage (2d); (v) fraction of existing to total home sales in percentage (2e); (vi) construction in thousands of units (2f); (vii) construction and development loans outstanding, deflated in millions of dollars (2g). The data sources are described in detail in the text in section 4.1. Fitted values are obtained by regressing each series on a constant and linear time trend.*

Figure 2: The 2012 — 2019 housing market recovery

equilibrium. They summarize measures of liquidity on the housing and credit markets, as well as inform on the search costs for buyers, sellers, financiers, and developers. We are also able to use them to back out information on the bargaining power η and on the elasticity of the cost function for buyers, γ, which are important for quantifying the magnitude of the credit channel and for identifying the recovered shocks in our numerical exercise to follow. Below we provide a brief description of the calibration strategy and in the appendix we provide a detailed description of how model parameters are obtained using the data targets.

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. 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 2.25% of existing home prices which is consistent with the evidence on realtor fees in Barwick, Pathak, and Wong (2017) and 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 (2021) 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%.[19] Next, we use data on the debt to equity ratio for real estate developer firms to calibrate the construction costs in the model, k.[20] Next, we use information on credit availability for firms in order to calibrate the credit-finding rate $q(\phi)$. Gabrovski *et al.* (2023) report that, using data from the National Federation of Independent Business (NFIB) Small Business Survey, on average 30% of firms had their borrowing needs satisfied in the previous quarter. Thus, we set $q(\phi) = 0.3566$.[21] Lastly, our calibration strategy thus far pins down the buyers' search cost $c^B(b)$, but not the individual parameters $\bar{c}$ and γ. We calibrate γ according to the strategy below and normalize $\bar{c} = 1$.[22]

[19]The data series we use is the Moody's Seasoned Aaa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity from the Interest Rates Spreads release of the Federal Reserve Bank of St. Luis.

[20]In particular, we use the data on the market debt-to-equity ratio adjusted for leases, reported by Aswath Damodaran. It's average is 94.7%. It can be found at `http://people.stern.nyu.edu/adamodar/New_Home_Page/dataarchived.html`.

[21]Given that meetings follow a Poisson process, the chance a firm did not get its borrowing needs satisfied is $e^{-q(\phi)} = 0.7$. This yields an average credit search duration of about 10 months.

[22]In particular, since $c^B(b) = \bar{c}b^\gamma$, it follows that $b = \bar{c}^{-1/\gamma}c^B(b)^{1/\gamma}$. Thus, the value of $\bar{c}$ governs the absolute size of the market, i.e. the calibrated number of buyers. However, since our model features entry of both buyers and sellers, as well as free entry for financiers the absolute size of the market is inconsequential. This is analogous to the normalization in search models of the labor market, where one commonly assumes the labor force is 1 and to search models with money, where one usually assumes the mass of households is unit as well. Alternatively, we could have normalized $b = 1$ as in Gabrovski and Ortego-Marti (2019), but again this is inconsequential for our calibration. For further details see Appendix B.

We need one more data target in order to pin down γ. Since the equations which describe the model equilibrium only pin down $c^B(b)$, one must identify γ by looking at the implied model deviations from steady state. Indeed, this is the strategy that both Gabrovski and Ortego-Marti (2019) and Gabrovski and Ortego-Marti (2022) use to calibrate the elasticity of the buyers' cost function in this class of models. Thus, we follow the approach in Gabrovski and Ortego-Marti (2022) and use evidence on the empirical slope of the Beveridge Curve to inform on the value of γ. In particular, we back out the response in buyers on the housing market following an increase in housing vacancy using the available data on vacancies and sales we outlined in section 4.1.[23] Specifically, in our model sales$= bm(\theta)$ and $\theta = b/v$, so one can back out an empirical series for buyers as $b = v[\text{sales}/(\mu v)]^{1/(1-\alpha)}$ (using the calibrated values for μ and α). Next, we regress the cyclical component of the series for buyers on that for vacancies and a constant.[24] The resulting elasticity is 0.2783. We then set $\gamma = 1.499$, so that the model-implied elasticity $(\mathrm{d}b/b)/(\mathrm{d}v/v)$ following a 1% increase in ε matches the empirical one. Table 2 summarizes our calibrated parameter values and Table 3 summarizes the calibrated equilibrium variables.

In the calibrated equilibrium prices for existing homes are higher than those for newly built houses. The reason for that is developers have to make loan repayments ρ while searching for a buyer, whereas sellers of existing homes do not. This lowers the value of the outside option for the developer, V_1, in the bargaining game with the buyer and so the negotiated price p^N is lower than that negotiated with a seller of an existing home, p^E. In terms of magnitudes, the average loan cost $\rho/[\theta m(\theta)]$ is 17.63, which is 35% of the house price. The resulting markup for the developer, $p^N/[k + \frac{\rho}{\theta m(\theta)} + \frac{c^S}{\theta m(\theta)}] - 1$ is 47%, which is close to the 46% reported in De Loecker *et al.* (2020) for the year 2012.

4.3 Matching the stylized facts

Our main goal is to understand the dynamics of the housing market recovery which gave rise to the stylized empirical facts we highlighted in section 4.1, and in particular the importance of the credit channel for that recovery. To this end, we use the calibrated model as a laboratory that allows us to recover unobserved changes that have occurred in the market during the 2012 — 2019 period, as well as conduct a series of counter-factual exercises. Since our focus is on

[23]Ideally, one would gather data on vacancies and buyers, but unfortunately no such data is available (see Gabrovski and Ortego-Marti (2024)). Gabrovski and Ortego-Marti (2024) use a similar approach to estimate the empirical slope of the Beveridge Curve by focusing on vacancies and time-to-sell instead of sales.

[24]To obtain the cyclical component we first take logs and then HP-filter the series with a smoothing parameter of 129,600. Note that since it is available, we use monthly data for both vacancies and sales.

Externally calibrated parameters			
Preferences/Technology	Parameter	Value	Source/Target
Utility	ε	1	Normalization
Buyer cost scale parameter	$\bar{c}$	1	Normalization
Discount rate	r	0.0086	Annual interest rate= 3.5%
Elasticity of Housing Market Matching Function	α	0.16	Genesove and Han (2012)
Elasticity of Credit Market Matching Function	α_f	0.5	Petrosky-Nadeau and Wasmer (2013)
Destruction rate	δ	0.004	Van Nieuwerburgh and Weill (2010)
Bargaining power in housing market	β	0.5	Ngai and Sheedy (2020)

Internally calibrated parameters			
Preferences/Technology	Parameter	Value	Source/Target
Separation Rate	s	0.0238	Tenure= 9 years
Efficiency of Housing Market Matching Function	μ	0.7129	TTS= 1.4027 quarters
Efficiency of Credit Market Matching Function	μ_f	0.0379	TTB=TTS
Seller cost	c^S	1.068	Realtor fee = 2.25% of price
Developer cost	c^D	5.570	Average buyer cost= 8% of price
Financier cost	c^F	0.0684	Moody's AAA-Treasury Bill spread = 1.8617%
Bargaining power in credit market	η	0.4792	Frac. of firms with satisfied borrowing needs = 30%
Construction cost	k	14.792	Debt-to-equity ratio = 94.7%
Buyer cost function elasticity parameter	γ	1.499	Elasticity of buyers wrt vacancies = 0.2783

Note.- *Table 2 summarizes the calibrated parameter values and their sources/targets. The top panel depicts the externally set parameters and their sources. The bottom panel shows the internally calibrated ones and the empirical targets used to recover each parameter. A detailed description of how we obtain each parameter from the targets is included in Appendix B.*

Table 2: Calibration

Name	Variable	Equilibrium Value
New Home Price	p^N	49.82
Existing Home Price	p^E	66.59
Housing Market Tightness	θ	1
Credit Market Tightness	ϕ	0.01
Buyer's Search Cost	$c^B(b)$	3.66
Repayment	ρ	12.57

Note.- *Table 3 reports the values of selected model variables at the calibrated steady state equilibrium.*

Table 3: Calibrated equilibrium values

the trend behavior of the market, rather than short-term fluctuations we conduct our analysis as a comparison of steady states. That is, we take the model calibrated to the 2012 market and ask "what changes in housing demand, housing supply, and the ease with which developers find credit must have occurred for us to observe the stylized facts?" We find the answer by allowing several key model parameters to change so that the model steady state changes match the empirical facts. In this regard our analysis is analogous to the numerical explorations in Gabrovski and Ortego-Marti (2021) and Ngai and Sheedy (2020).

The key model parameters which we allow to adjust are chosen so that we indeed capture changes in housing demand, housing supply, and financing conditions for developers. We capture housing demand through shocking ε. This is a common way to generate fluctuations in demand within the literature (Diaz and Jerez, 2013; Gabrovski and Ortego-Marti, 2019, 2021) and also a natural way within our model to capture changes in preferences towards homeownership, changes in disposal income, or a change in speculative beliefs. To capture changes in housing supply we focus on construction costs, k. Indeed, there is empirical evidence that construction costs and land use regulations have increased significantly over the period.[25] Thus, we allow for k to vary captures a potentially important empirical regularity. Supply of homes for sale within the model also comes in the form of existing houses for sale. Thus, we allow for s to adjust to capture the compositional changes in the ratio of existing to new home sales coming from changes in housing tenure. This is important for capturing the importance of the credit channel since the supply of existing homes competes with that for newly build houses.

To capture changes in credit conditions for developers we allow c^D to adjust. This is the credit shock. We choose this parameter for three reasons. First, these costs are central to the credit channel in our paper. Second, changes in financial conditions over the period were potentially important for the ease with which developers can embark on new construction and development projects which is central to the supply of new houses and liquidity on the market as a whole. Third, there is evidence to suggest that developers have faced tighter credit constraints over the 2012:1 — 2019:4 period. For example, there is evidence of tightening standards for commercial real estate loans, especially after 2014.[26] From the lens of the model such tightening standards directly translate to higher search costs c^D. Survey evidence on the increasing costs for developers associated with acquiring the credit is also available from

[25]For example, there is evidence on increasing 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); 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); increasing land regulations (Ganong and Shoag, 2017; Glaeser and Ward, 2009).

[26]See the series Net Percentage of Domestic Banks Tightening Standards for Commercial Real Estate Loans with Construction and Land Development Purposes from the Senior Loan Officer Opinion Survey on Bank Lending Practices of the Board of Governors of the Federal Reserve System.

the National Association of Home Builders.[27] For example, of those firms which perceived the availability of new loans to be worse during a particular quarter, more than a third cited increasing documentation requirement as a cause. Through the lens of our model this also translates to an increase in c^D.

Lastly, developers search for both credit and, once they have built the house, buyers. We want to be careful in our numerical exercise and not attribute any changes in the search costs on the housing market to increases in the costs associated with securing a credit line and vice versa. Thus, we allow the search costs in the housing market, c^S, to adjust so that the average search cost $c^S/[\theta m(\theta)]$ remains at 2.25% of the house price. This captures the empirical regularity that realtor fees have remained constant over time (Barwick, Pathak, and Wong, 2017) and allows to more cleanly identify the credit shock.

Thus, the mechanics of our quantitative exercise are as follows. We take the calibrated parameter values from section 4.2 for all parameters, except for $\varepsilon, k, c^S, c^D, s$. We then re-calibrate these parameters so that the changes in prices, time-to-sell, the fraction of new to existing home sales, the amount of loans outstanding, and realtor fees between this new calibrated steady state and the original calibrated steady state exactly match the changes from the stylized facts. We then report the percentage change in $\varepsilon, k, c^S, c^D, s$ from the initial calibrated equilibrium to the new calibrated equilibrium as our recovered parameter shocks.

Table 4 presents our findings. First, we observe that the utility from homeownership increased by 39%. At first glance this may appear large, but it is smaller than the 45% increase in prices which we use to identify it. It is also much smaller than the 63% increase that Gabrovski and Ortego-Marti (2021) find during the housing boom from 2001 to 2006 and within the ballpark of the 21% that Ngai and Sheedy (2020) calibrate in their model for the homeownership utility increase for the 1995 - 2003 period. Next, the construction cost increased by 86%. Rising construction costs are in line with the empirical evidence on increasing land regulation (Ganong and Shoag, 2017; Glaeser and Ward, 2009) and increasing construction costs and wages.[28] Moreover, their magnitude is similar to the magnitude of the empirically observed 40% increase in construction costs and 65% increase in residential land prices.[29] A major change in the supply for housing appears to be compositional: the separations rate decreased by about a quarter. This decrease in separations is necessary in order to reconcile the stylized facts on construction and fraction of existing to total home sales: since new construction only accounts for about 15% of sales in the initial equilibrium even a 67% increase in it is not enough to match the

[27]See the 2024Q1 Survey on Acquisition, Development & Construction Financing available on the NAHB website and the historical information contained therein.

[28]See the Employment Cost Index for Wages and Salaries for Private Industry Workers in Construction released by the U.S. Bureau of Labor Statistics and Producer Price Index by Commodity: Special Indexes: Construction Materials released by the U.S. Bureau of Labor Statistics.

[29]See the Census Bureau's construction price indexes for New Single-Family Houses Under Construction and Davis, Larson, Oliner and Shui (2021)

Variable	Percentage Change	Target Series Percentage Change
ε	38.72%	Prices
k	85.60%	Time-to-sell
c^S	108.66%	Realtor fees
c^D	81.11%	Construction and Development Loans
s	-25.77%	Existing to Total Home Sales

Note.- Table 4 reports the model-implied changes in the (i) utility of home-ownership, ε, (ii) construction costs, k, (iii) seller search costs, c^S, (iv) developer financing search costs, c^D, (v) separation rate, s. They are derived by calibrating the model to the initial 2012 equilibrium calibrated in section 4.2 and letting the 5 parameters vary so that the steady state change in (i) prices, (ii) time-to-sell, (iii) realtor fees, (iv) construction and development loans, (v) fraction of existing to total home sales match those in the stylized facts from section 4.1.

Table 4: Size of recovered shocks

decrease in the fraction alone. The decrease in the separations rate implies the average housing tenure increased from 9 to 11 and a half years, which is within the range of estimates in the literature.[30] Given the increase in prices and liquidity on the market, the seller search costs more than doubled to account for the stable realtor commissions. Lastly, the almost doubling of construction loans implies an 81% increase in developer search costs, c^D.

4.4 Model fit

Before turning to the results of our numerical exercise, we find it instructive to evaluate the model's fit. In particular, we highlight several un-targeted moments relating to both the calibration and the stylized facts from section 4.1. We deem these moments to be of interest, but not as important to match exactly as the moments we match in our calibration. Nonetheless, our model does quite well in matching these un-targeted moments (Table 5). It reproduces a vacancy rate and markup slightly above their data counterparts but within the same ballpark. The model-implied value for the existing to total home sales is a bit lower than its data counterpart, but within 10% of it. When it comes to generating the stylized facts, the model is able to reproduce more than 2/3 of the empirical variation in construction and more than 3/4 of that in sales. The model-implied vacancy rate does drop a bit more than that in the data but it is still not too far off. 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.

[30] For example, Diaz and Jerez (2013) report a median tenure of 9 years using data from the National Association of Realtors; Ngai and Sheedy (2020) finds tenure length of 16 and a half years using data from the American Housing Survey.

Moments relating to the calibrated equilibrium			
Moment	Expression	Model	Data
Existing to Total Home Sales	π	85.12%	92.79%
Vacancy Rate	$\frac{v}{v+h}$	3.75%	2.2%
Developer Markup	$\frac{p^N}{k+\frac{\rho}{\theta m(\theta)}+\frac{c^S}{\theta m(\theta)}} - 1$	46.86%	46%

Moments relating to the stylized facts			
Moment	Expression	Model	Data
Construction	$v^N[\delta + \theta m(\theta)]$	46.29%	66.76%
Sales	$bm(\theta)$	16.01%	21.17%
Vacancy Rate	$\frac{v}{v+h}$	−44.60%	−34.35%

Note.- Table 5 compares model moments to those in the data for moments not targeted in the calibration nor in the procedure used to match the stylized facts. For the moments relating to the stylized facts, the last column reports the findings from section 4.1. For the moments relating to the calibration, the empirical moments for the fraction of existing to total home sales and for the vacancy rate the data point is the fitted value for 2012:1 from regressing the series on a constant and linear time trend. For the developer markup we use the markup reported in De Loecker et al. (2020) for the year 2012.

Table 5: Un-targeted moments

4.5 Numerical results

We now turn to our numerical results. First, we analyze the model-implied change in variables of interest, especially those most directly affected by the credit channel. Table 6 summarizes the changes in equilibrium variables of interest. Since the market recovery was characterized by an increase in the utility from housing, there were extra incentives for entry into the construction sector. This, together with the relatively higher search costs c^D, created opportunities for financiers, which increased the funds made available for loans. As a result finding loans became easier and the average length of credit search for developers decreased by about 25%. It is important to observe that our analysis predicts a tightening of credit standards as captured by an increase in c^D and, at the same time, more availability of credit as captured by an increase (decrease) in $q(\phi)$ (ϕ). At first glance these might appear contradictory, but they are not. In fact, there is empirical evidence to support both results. As we highlighted in section 4.3 during our sample period banks were tightening credit standards for construction and development loans as reported in the Senior Loan Officer Opinion Survey on Bank Lending Practices. At the same time loan officers were reporting weaker credit demand, consistent with a decrease in the market tightness, ϕ. Similarly, survey data from the NAHB indicates that real estate developers overwhelmingly perceived better availability of loans for construction and development during our sample period.[31] Overall, the two effects of tightening lending

[31]The Senior Loan Officer Opinion Survey on Bank Lending Practices release is reported by the Board of Governors of the Federal Reserve System. For data on tightening standards we look at the series Net Percentage of Domestic Respondents Tightening Standards for Commercial Real Estate Loans and for data on loan demand at the series Net Percentage of Domestic Banks Reporting Stronger Demand for Commercial Real Estate Loans with Construction and Land Development Purposes. For the period 2013:4 (first period data is available)

Variable	Expression	Equilibrium Change
Credit Search Duration	$1/q(\phi)$	-25.69%
Average Credit Finding Cost	$\frac{c^D}{q(\phi)}$	34.58%
Average House Finding Cost	$\frac{c^B(b)}{m(\theta)}$	48.18%
Developer Markup	$\frac{p^N}{k+\frac{\rho}{\theta m(\theta)}+\frac{c_S}{\theta m(\theta)}} - 1$	-14.59%
Average Loan Costs	$\frac{\rho}{\theta m(\theta)}$	33.46%
Vacancy Costs	$\frac{c^D}{q(\phi)} + \frac{c^F}{\phi q(\phi)} + \frac{c^S+c^F}{\theta m(\theta)} + k$	50.20%

Note.- Table 6 reports the changes in steady state equilibrium values for variables of interest. The changes are calculated by taking the percent change from the equilibrium calibrated in section 4.2 and the equilibrium under the new values of ε, k, c^S, c^D, s. The stylized facts in the last column are those from section 4.1.

Table 6: Model-implied changes during the 2012 — 2019 market recovery

standards and shorter credit search duration lead to about 35% increase in expected credit finding costs: an increase that is a bit less than the increase in prices, but still sizeable.

The average loan costs increased as well. Even though houses were selling faster, by the end of the recovery period the average loan costs developers paid increased by a third. This is mainly due to the larger loan principal amount, since k almost doubled. In fact, the average loan costs per unit borrowed, $\rho/[\theta m(\theta)k]$ decreased by about 50%. At the same time, the increase in construction costs also lead to a decrease in the markup developers were charging. Lastly, the increase in construction and search costs for developers lead to about 50% increase in the total vacancy costs (the sum of construction and total search costs). Breaking this down further, the contribution of construction costs to the total costs increased from 30% to 37%, whereas the costs that developers pay decreased from 70% to 63%.[32]

Overall, our numerical exercise suggests that developer costs associated with finding credit increased during the 2012:1 — 2019:4 period and that they are a sizeable fraction of the total costs to create a vacancy. This suggests that the credit channel we study is quantitatively important for explaining the dynamics of the housing market during the recovery. We explore further the importance of that channel by conducting three counter-factual exercises. First, we let ε, k, c^S, s all adjust to their 2019:4 levels, but we keep c^D fixed at its initial 2012:1 value; second, we do the same but keep c^S constant; third, we keep s fixed at its initial value. Table 7 depicts our counter-factual exercises.

through 2019:4 the net percent of banks reporting tightening standards begins at about -10% and quickly becomes positive, exhibiting an upward trend, whereas the net percent reporting stronger demand begins at about 30% and exhibits a downward trend, ending at -9.6%. The NAHB survey data is contained within their Survey on Acquisition, Development & Construction Financing. Specifically, their Net Easing index which calculates the share of respondents who say availability of new loans is "better" less the share of respondents who say it is "worse" than the previous quarter.

[32]To be precise, the costs that developers pay for the vacancy are $c^D/q(\phi) + (c^S + \rho)/[\theta m(\theta)]$.

No Change in Frictions Shock, c^D					
Variable	Price	Time-to-Sell	Construction	Vacancy Rate	Sales
Counter-factual Change	25.09%	55.29%	134.6%	20.09%	81.42%
No Change in Seller Cost Shock, c^S					
Variable	Price	Time-to-Sell	Construction	Vacancy Rate	Sales
Counter-factual Change	44.53%	7.44%	70.53%	−15.75%	33.73%
No Change in Separation Shock, s					
Variable	Price	Time-to-Sell	Construction	Vacancy Rate	Sales
Counter-factual Change	45.48%	−42.16%	−7.16%	−41.23%	−5.67%

Note.- Table 7 reports the results of our counter-factual exercises. The top panel depicts the implied changes in prices, time-to-sell, construction, the vacancy rate, and sales when ε, k, c^S, s are at their 2019 calibrated equilibrium levels, but c^D is held fixed at its 2012 level. The second panel repeats the exercise, but holds fixed c^S instead. In the third one, s is held fixed at its initial 2012 level. Overall, the shocks in all three of c^D, c^S, s had sizeable impact on market liquidity, but only the credit shock mattered for prices. Absent the credit shock, prices would have increased only by about half what we see in the data.

Table 7: Counter-factual exercises

In our first exercise of keeping c^D constant we ask the question "What would the market recovery have looked like if banks did not tighten their lending standards?" Absent the credit shock, we see that construction more than doubles. This is because the total vacancy costs are now relatively lower. This relatively larger increase in construction leads to about twenty percent increase in the vacancy rate and a 50% increase in 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 vacancy 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 price increases during the 2012 — 2019 period. Lastly, since prices would have increased relatively less, this would have lead to an almost doubling of sales.

In our second counter-factual exercise, we keep the seller's search costs c^S fixed at their 2012 level. This allows us to see what the market would have looked like if realtor fees did not keep pace with the increase in prices. We see that the relatively cheaper vacancy costs would have lead to a slightly larger increase in construction and a slightly lower decrease in the vacancy rate. Intuitively, this is the case because lower costs would have incentivized more entry. The increase in construction and vacancies would have in turn increased the time-to-sell slightly and sales would have increased by about a third, compared to the 22% increase we observed in the data. The relatively lower seller costs however, would have had very little impact on prices. This result is in line with Gabrovski and Ortego-Marti (2019) whose model predicts the equilibrium price is independent of the search costs and Gabrovski *et al.* (2024) who show that changes in realtor fees have an impact on the volume of sales but not on prices. We can conclude that it was indeed the credit channel that contributed to the observed increase in prices and not simply a general rise in search costs.

In our third and final counter-factual exercise, when we keep the separation rate fixed at its initial level, we see that the change of prices, time-to-sell, and the vacancy rate is very close to the empirically observed. Thus, we conclude that these variables are more tightly linked to vacancy 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 7% 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 decrease in construction lead to an overall decrease in vacancies which in turn lead to a decrease in the sales. On the whole, the competition developers faced from existing homes for sale mattered for market liquidity but not for prices.

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 counter-factuals 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.

We envision the following extensions to our paper. First, our framework 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 did not matter much for the observed price increase, it would be interesting to understand the determinants of house separations. This is in part because the separation shock mattered for liquidity in the market. In current work in progress (Gabrovski *et al.*, 2024), 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. Second, our paper treats the tightening of lending standards as a shock that developers take as given. It would be interesting to endogenize lenders' lending standards and credit supply. This exercise is, however, beyond the scope of this paper and left for future research. Finally, our study describes the effect of credit frictions faced by developers on the housing market. The equilibrium is, however, inefficient even if the HMP condition holds. Our aim for future research is to analyze efficiency in detail to assess whether we observe over- or under-lending in the credit market, and how credit market policies can restore efficiency.

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Variable	Variable Change	Data	Data Change
ε	33.53%	Prices	40.51%
k	75.85%	Time-to-sell	−33.61%
c^S	112.84%	Realtor fees	
c^D	70.80%	Construction and Development Loans	57.82%
s	−25.06%	Existing to Total Home Sales	−4.38%
		Sales	19.70%
		Construction	65.26%
		Vacancy Rate	−32.10%

Note.- Table 8 reports the stylized facts calculated as the percentage change between the average value of the series of interest for 2012 and the average value for 2019. The model-implied changes in the (i) utility of home-ownership, ε, (ii) construction costs, k, (iii) seller search costs, c^S, (iv) developer financing search costs, c^D, (v) separation rate, s are also reported. They are derived by calibrating the model to the initial 2012 equilibrium and letting the 5 parameters vary so that the steady state change in (i) prices, (ii) time-to-sell, (iii) realtor fees, (iv) construction and development loans, (v) fraction of existing to total home sales match those in the stylized facts from the last column in the table.

Table 8: Stylized facts and recovered shocks, robustness

A Appendix: Stylized facts: robustness exercise

In our main empirical exercise, we take the housing market variables of interest and regress each on a constant and a linear time trend. We then look at the percentage change between the first and last fitted value to derive the stylized facts. Thus we are able to abstract away the cyclical fluctuations in the data and focus on the trend behavior. An alternative approach is to follow Gabrovski and Ortego-Marti (2021) and take the percentage change in the average values of the variables during 2019 and 2012 respectively. In this appendix we follow this alternative approach and show that our numerical conclusions remain quantitatively similar with some minor exceptions.

Table 8 summarizes the stylized facts using the alternative approach. The changes in all variables, except for loans are quantitatively similar. For construction and development loans the change under the alternative approach is only about two thirds that under the baseline approach outlined in the text. This is mainly due to the fact that lending didn't reach the bottom until 2013, so the alternative approach understates the size of the recovery in the series. The table also reports the recovered shocks in the utility of home-ownership, construction costs, seller search costs, developer financing costs, and the separation rate. Their magnitude is smaller than that in the main exercise in the text, but still comparable.[33] For example, the magnitude of the financial shock is 71% under the alternative approach and 81% in the benchmark.

[33] We should note that we re-calibrate both the initial and end equilibria.

Variable	Expression	Equilibrium Change
Credit Search Duration	$1/q(\phi)$	-23.48%
Average Credit Finding Cost	$\frac{c^D}{q(\phi)}$	30.69%
Average House Finding Cost	$\frac{c^B(b)}{m(\theta)}$	38.89%
Developer Markup	$\frac{p^N}{k+\frac{\rho}{\theta m(\theta)}+\frac{c_S}{\theta m(\theta)}} - 1$	-14.54%
Average Loan Costs	$\frac{\rho}{\theta m(\theta)}$	29.01%
Vacancy Costs	$\frac{c^D}{q(\phi)} + \frac{c^F}{\phi q(\phi)} + \frac{c^S+c^F}{\theta m(\theta)} + k$	45.34%

Note.- Table 9 reports the changes in steady state equilibrium values for variables of interest under the robustness exercise.

Table 9: Model-implied changes during the 2012 — 2019 market recovery

Tables 9 and 10 report the numerical results under the alternative approach. The equilibrium changes in the variables of interest are quantitatively similar and so are the findings from the counter-factual exercises. The only notable changes are when it comes to the counter-factual exercise when we keep c^D constant. Due to the smaller size of the financial shock, the implied counter-factual increases in time-to-sell, construction, vacancy rate, and sales are smaller as well. However, the counter-factual increase for prices is similar to that in the baseline exercise from the text.

No Change in Frictions Shock, c^D					
Variable	Price	Time-to-Sell	Construction	Vacancy Rate	Sales
Counter-factual Change	23.52%	34.90%	104.3%	5.68%	60.04%
No Change in Seller Cost Shock, c^S					
Variable	Price	Time-to-Sell	Construction	Vacancy Rate	Sales
Counter-factual Change	40.27%	0.40%	56.00%	-20.39%	23.70%
No Change in Separation Shock, s					
Variable	Price	Time-to-Sell	Construction	Vacancy Rate	Sales
Counter-factual Change	40.96%	-44.71%	-12.21%	-43.58%	-10.42%

Note.- Table 10 reports the results counter-factual changes in prices, time-to-sell, construction, the vacancy rate, and sales under robustness exercise.

Table 10: Counter-factual exercise

B Appendix: Calibration details

Recall that the parameters $\{r, \delta, s, \alpha, \beta\}$ are all set according to external targets and ε is normalized to unity. To calibrate the rest of the parameters internally, we use 8 empirical targets: (i) time-to-sell= 1.4027; (ii) time-to-buy = time-to-sell; (iii) average buyers' cost = 8% of the average house price; (iv) average seller's cost = 2.25% of the price for existing homes; (v) the spread between the yield on Moody's Seasoned Aaa Corporate Bond and the yield on 10-year constant maturity Treasury bonds is 1.8617%; (vi) debt-to-equity is 94.7%; (vii) 30% of firms had their borrowing needs satisfied in the previous quarter; (viii) the empirical slope of the Beveridge Curve is 0.2783.[34]

We begin by backing out θ. Since time-to-buy is $1/m(\theta)$ and time-to-sell is $1/[\theta m(\theta)]$ and the two are equal, it follows that $\theta = 1$. This, together with $\alpha = 0.16$ yields $\mu = 0.71294$. Next, equation (36) yields $\pi = 0.85122$. The average cost for the seller is $c_S/[\theta m(\theta)]$ which is set to $0.0225p^E$. Thus, $c_S = 0.016041p^E$. Plugging this into (31) solves for the equilibrium price of existing homes, $p^E = 66.59$, thus $c_S = 1.0682$.

To solve for the average price p and the buyers' search cost $c^B(b)$, we turn to the bellman equation for buyers, (7). Substituting $B = 0$ yields

$$\frac{c^B(b)}{m(\theta)} = H - \pi p^E - (1-\pi)p^N \tag{A1}$$

$$\frac{c^B(b)}{m(\theta)} = \frac{\varepsilon + sV^E}{r+s+\delta} - p, \tag{A2}$$

where the second line makes use of (20). From equation (5) it follows that $V^E = [\theta m(\theta)p^E - c_S]/[r + \delta + \theta m(\theta)]$, so

$$\frac{c^B(b)}{m(\theta)} = \frac{\varepsilon + s\frac{\theta m(\theta)p^E - c_S}{r+\delta+\theta m(\theta)}}{r+s+\delta} - p. \tag{A3}$$

(A3) together with moment (iii) solve for $p = 64.097$ and $c^B(b) = 3.6558$. Using the information on p^E, p, π, we derive $p^N = 49.818$.

In our economy equity for developers is V_1^N and debt is k. Thus, $k/V_1^N = 0.947$. Then, using (13), it follows that $c_D/q(\phi) + k = (1 + 0.947)c_D/q(\phi)$. This, combined with (32) solves for $c_D/q(\theta) = 15.62$ and $k = 14.792$. Since $q(\phi)$ is calibrated to 0.3566, this yields $c_D = 5.57$. The search cost for financiers is c^F, which we interpret as a liquidity cost for providing the loan, following Gabrovski and Ortego-Marti (2021). Thus, we pick c^F to match the spread between the yield on Moody's Seasoned Aaa Corporate Bond and the yield on 10-year constant maturity Treasury bonds. Since our calibration period is quarterly, we set c^F to be 0.46221% of

[34] See the main text in section 4.2 for a discussion on the targets and their sources.

the principal k or $c^F = 0.068369$. To solve for η we use (18), which yields $\eta = 0.47924$. Having recovered η we can solve for the equilibrium credit market tightness from (28) as $\phi = 0.011296$. This allows us to back out $\mu_f = 0.037901$ and solve for the equilibrium repayment $\rho = 12.57$ from (29).

This leaves us with two parameters to calibrate: $\bar{c}$ and γ. Firstly, observe that we have completely characterized the steady state equilibrium in the economy, aside from the masses of buyers, vacancies, developers, and homeowners. Thus, the tuple $\{\phi, \theta, \rho, p^N, p^E, \pi\}$ is entirely pinned down by the value of $c^B(b)$ and is independent of the value of b, whereas the tuple $\{b, D, h, v^N, v^E, v\}$ depends on both the search costs $c^B(b)$ and the mass of buyers b. In fact, the tuple $\{\phi, \theta, \rho, p^N, p^E, \pi\}$ is independent of the value of any of the masses of agents. This structure is standard for this class of models of the housing market (see, for example Gabrovski and Ortego-Marti (2019), Gabrovski and Ortego-Marti (2021)). It also arises naturally in search models of the labor market, e.g. the labor market tightness and wages depend on the unemployment rate, but not on the absolute number of unemployed people or the size of the labor force. Hence, one can normalize the size of buyers in equilibrium to some number, say 1. This is, for example the approach in Gabrovski and Ortego-Marti (2019). An alternative is to normalize the scale parameter of the cost function as in Gabrovski and Ortego-Marti (2021). Both approaches are isomorphic. Here we employ the latter and set $\bar{c} = 1$.

Thus, we are left with γ as the only un-recovered parameter. Similar arguments to the preceding paragraph imply that the tuple $\{\phi, \theta, \rho, p^N, p^E, \pi\}$ does not depend on γ per se but rather on the search cost $c^B(b)$. Furthermore, having normalized $\bar{c}$, we have normalized the size of the market and so the tuple $\{b, D, h, v^N, v^E, v\}$ does not provide information on γ and vice versa. To calibrate γ one needs to instead look at elasticities within the model. Thus, we follow the calibration strategy in Gabrovski and Ortego-Marti (2022) and pick γ such that the model elasticity $(\mathrm{d}b/b)/(\mathrm{d}v)/v$ following a 1% increase in ε matches the elasticity in the data.[35] This yields $\gamma = 1.499$.

[35]The text in section 4.2 details how we obtain an estimate of the empirical elasticity.