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How Do Foreclosures Exacerbate Housing Downturns?

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ABSTRACT

This paper uses a structural model to show that foreclosures played a crucial role in exacerbating the recent housing bust and to analyze foreclosure mitigation policy. We consider a dynamic search model in which foreclosures freeze the market for non-foreclosures and reduce price and sales volume by eroding lender equity, destroying the credit of potential buyers, and making buyers more selective. These effects cause price-default spirals that amplify an initial shock and help the model fit both national and cross-sectional moments better than a model without foreclosure. When calibrated to the recent bust, the model reveals that the amplification generated by foreclosures is significant: Ruined credit and choosey buyers account for 25.4 percent of the total decline in non-distressed prices and lender losses account for an additional 22.6 percent. For policy, we find that principal reduction is less cost effective than lender equity injections or introducing a single seller that holds foreclosures off the market until demand rebounds. We also show that policies that slow down the pace of foreclosures can be counterproductive.

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A data appendix is available at <http://www.nber.org/data-appendix/w26216>

Foreclosures were one of the dominant features of the U.S. housing downturn. From 2006 through 2013, approximately eight percent of the owner-occupied housing stock experienced a foreclosure.¹ Although the wave of foreclosures has subsided, understanding the role of foreclosures in housing downturns remains an important part of reformulating housing policy.

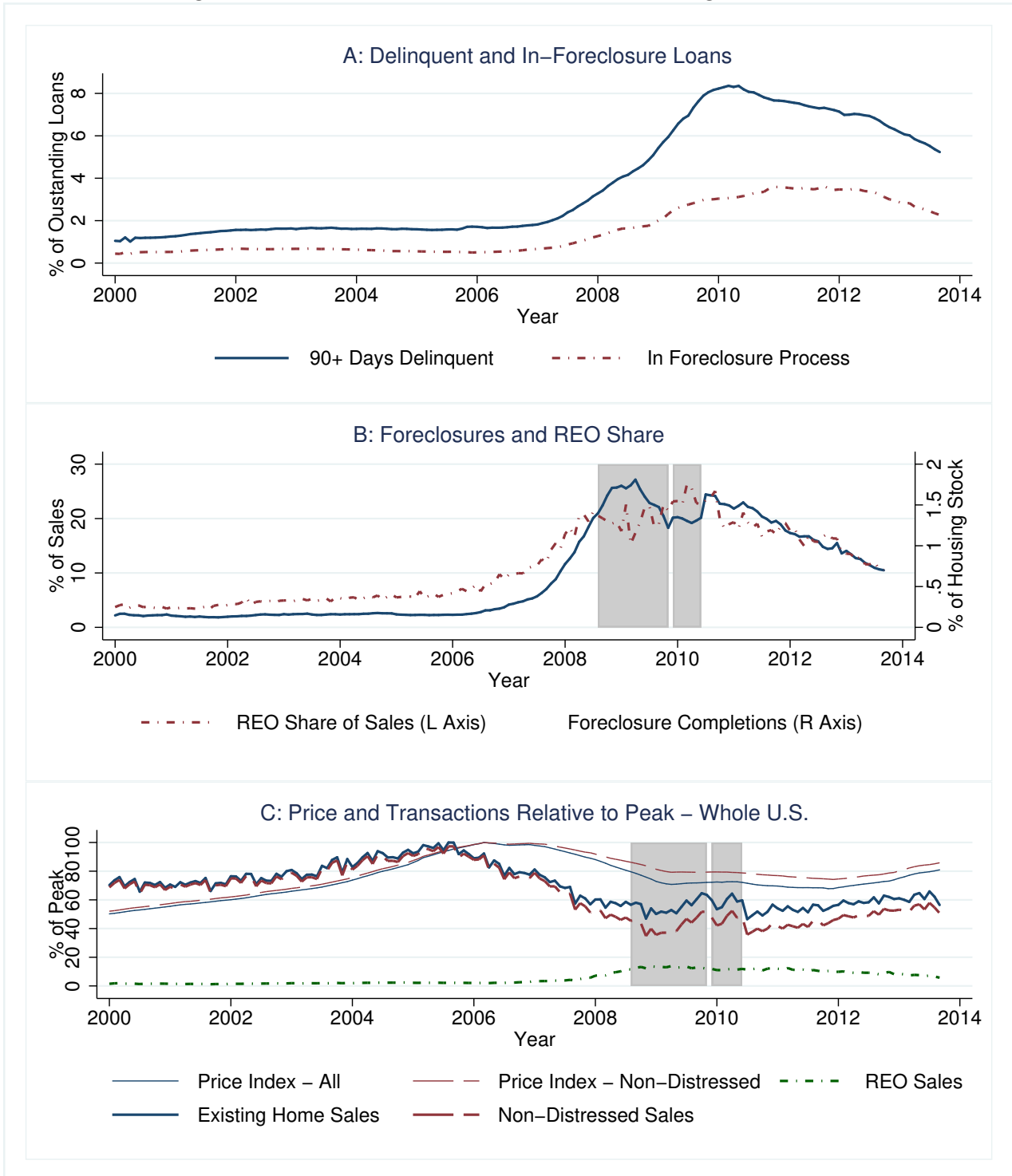
The behavior of the housing market concurrent with the wave of foreclosures is shown in Figure 1. Real Estate Owned (REO) sales — sales of foreclosed homes by lenders — made up over 20 percent of existing home sales nationally for four years. Non-foreclosure sales volume fell 65 percent as time to sale rose. Prices dropped considerably, with aggregate price indices plunging a third and non-distressed prices falling by a quarter.

This paper uses a structural model to argue that quantitatively matching national and cross-sectional features of the bust requires that foreclosures play a significant role in exacerbating the bust. Indeed, in our calibrated model we find that the effect of having more homeowners with a foreclosure flag on their credit record and increased buyer choosiness due to the presence of foreclosures together account for 25.4 percent of the total decline in non-distressed prices and that the reduction in lending stemming from default-induced lender losses accounts for an additional 22.6 percent. Our model implies that foreclosures have far greater equilibrium effects than those found in micro-econometric studies, which use highly localized fixed effects and absorb much of the city-level variation reduction in supply and demand that is at the heart of our structural analysis. The role played by foreclosures opens the door to various foreclosure mitigation policies, and we use our model to compare several such policies. Our policy analysis reveals that both lender equity injections and a government facility to strategically hold foreclosures off the market are highly effective, while principal reductions similar to those pursued by the Home Affordable Modification Program (HAMP) are less cost effective. Furthermore, if household liquidity shocks are persistent, slowing down foreclosures can prolong the bust to the point that doing so becomes counterproductive.

We analyze an equilibrium search model of the housing market with random moving shocks, undirected search, idiosyncratic house valuations, Nash bargaining over price, and endogenous conversion of owner-occupied homes to rental homes. The model builds on a literature on search frictions in the housing market, notably Wheaton (1990), Williams (1995), Krainer (2001), Novy-Marx (2009), Ngai and Tenreryo (2014), and Head et al. (2014). We add a mortgage market with a representative competitive lender facing a regulatory capital constraint and costly equity issuance, as well as mortgage default, whereby underwater homeowners default if hit by a liquidity shock, to this workhorse model. The mortgage sector in our model is related to recent research that models the interaction of the banking

¹All figures are based on data from CoreLogic described in detail below.

Figure 1: The Role of Foreclosures in the Housing Downturn



Notes: All data is seasonally adjusted national-level data from CoreLogic as described in the appendix. The grey bars in panels B and C show the periods in which the new homebuyer tax credit applied. In panel C, all sales counts are unsmoothed and normalized by the maximum monthly existing home sales while each price index is normalized by its separate maximum value.

sector and housing market, including Elenev et al. (2016), Greenwald et al. (2018), Hedlund (2016a, 2016b), Hendlund and Garriga (2019), and Paixao (2017).

Foreclosures have three distinguishing characteristics in our model: They cause losses for lenders and reduce lender equity, REO sellers have higher holding costs, and individuals who are foreclosed upon cannot immediately buy a new house. We show that foreclosures dry up the market for non-distressed sales and reduce volume and prices through three main equilibrium channels. First, reduced equity pushes lenders against their capital constraint and causes them to ration mortgage credit, which prevents some buyers from being pre-approved for a loan, which we call the lender rationing effect. Second, because foreclosed upon homeowners are for a time prevented from purchasing due to the foreclosure flag on their credit, foreclosures further reduce the number of buyers in the market relative to the number of sellers. We call this the foreclosure flag effect. Both the lender rationing effect and foreclosure flag effect result in an imbalance of buyers and sellers, reducing the probability that a seller contacts a buyer and lowering equilibrium prices. Typically, foreclosures are thought of as an expansion in supply; our model emphasizes that foreclosures also reduce demand. Third, the presence of distressed sellers increases the outside option to transacting for buyers, who have an elevated probability of being matched with a distressed seller next period and consequently become more selective. This choosey buyer effect endogenizes the degree of substitutability between REO and non-distressed sales.

In conjunction with the effect of foreclosures on prices, default amplifies the effects of negative shocks: An initial shock that reduces prices puts some homeowners under water and triggers foreclosures, which causes more price declines and in turn further default. Lock-in of underwater homeowners also impacts market equilibrium by keeping potential buyers and sellers out of the market, increasing the share of listings which are distressed. Endogenous conversion of owner-occupied units to renter-occupied in response to the increase in demand for rental units provides an important countervailing force.

We calibrate our model to match the nation-wide price decline, sales decline, REO share, and aggregate number of foreclosures from 2006 to 2013. The model fits a number of moments that are not direct calibration targets, including the decline in non-distressed prices. We use our model to quantitatively decompose the sources of the price decline. The choosey buyer and foreclosure flag effects together account for 32.3 percent of the decline in aggregate prices and 25.4 percent of the decline in non-distressed prices. We find that credit rationing associated with weakened lender balance sheets can explain an additional 27.1 percent of the decline in aggregate price indices and an additional 22.6 percent of the decline in non-distressed prices. Only 40.6 percent of the decline in aggregate prices and 52.0 percent of the decline in non-distressed prices is accounted for by an exogenous and permanent shock to

aggregate prices that we interpret as a bursting bubble. These amplification effects are far more substantial than those found by micro-econometric studies of foreclosure externalities. Such studies compare the highly local effect of foreclosures on neighboring prices and find minor effects; we find more substantial effects because our structural approach allows us to analyze market-wide equilibrium effects that are absorbed into the constant in micro studies.

To further validate the extent to which foreclosures can account for the bust, we add a parsimonious amount of cross-sectional heterogeneity to our model and evaluate its ability to explain cross-sectional moments relative to a model without default. In particular, we allow CBSAs to differ in their initial loan balance distribution, their unemployment rate, and the size of the preceding boom, assuming that the persistent component of the price decline in the bust is proportional to the boom. The calibrated model fits a number of cross-sectional moments despite the fact that most parameters are calibrated to pre-downturn moments and that these cross-sectional moments are not used in the calibration. In particular, the model does a good job of explaining quantitatively why cities with a larger boom had a more-than-proportionally-larger bust, which our model attributes to foreclosure. By contrast, a model without default does not explain these cross-sectional patterns and has a poorer fit because the size of the bust is proportional to the size of the boom.

Finally, we use the model to quantify the equilibrium impact of a number of government policies aimed at ameliorating the crisis, including principal reduction, equity injections, a facility to purchase foreclosures and hold them off the market until demand rebounds, and regulations to slow down the pace of foreclosures. To our knowledge, the only other papers to analyze foreclosure policy in a quantitative equilibrium model are Hedlund (2016b), who studies making non-recourse mortgages recourse, and Kaplan, Mitman, and Violante (2017), who consider debt forgiveness programs in a model with no price-default spiral. We first show that the effectiveness of slowing down the rate of foreclosure completions depends on the rate at which homeowners cure by regaining the ability to pay the mortgage or becoming above water. If the cure rate is fast enough, slowing down the rate of completions can be effective at limiting the amount of default. However, this policy also lengthens the crisis, which has a negative impact on prices. If the cure rate is sufficiently slow – which is likely the empirically-relevant case in a crisis – the effect of lengthening the crisis can dominate and slowing down the rate of completions can actually exacerbate the crisis. Second, we compare the equilibrium effects of three different government interventions to ameliorate the housing bust that operate on different margins: lender equity injections, homeowner principal reduction, and a government facility to purchase distressed homes, maintain them off the market, and re-introduce them once demand rebounds. We find the government facility to be highly cost-effective since since it directly addresses the imbalance of supply and demand

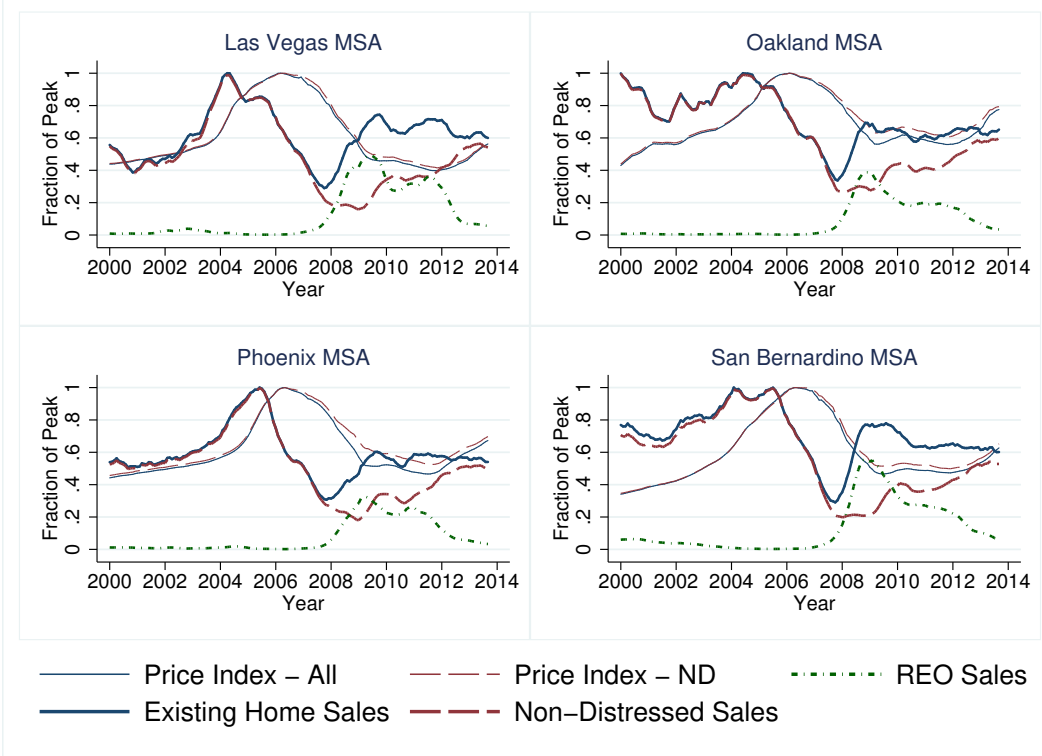
caused by foreclosures, which supports higher prices and reduces default. This in turn improves lender balance sheets, which further reduces the severity of the crisis. Government equity injections are also quite effective, while principal reductions have stronger aggregate effects than previous micro-econometric studies would suggest, but are still the least-cost effective of the policies we consider due to imperfect targeting.

Our analysis has a few limitations which one should be mindful of when interpreting the results. First, we consider only liquidity-driven default and do not consider a household's incentives to strategically default. Our model is a good approximation to the 2000s, as the literature has found that strategic default was limited in the crisis.² However, the absence of strategic default means that our model is not well suited to consider policies like the complete elimination of foreclosure, which would likely lead to widespread strategic default and cripple lender balance sheets. This pushes us to focus on *ex post* policies that would not dramatically change strategic default incentives if implemented carefully. Second, given our focus on a building a rich, structural framework of housing market dynamics and lender balance sheets, we do not fully model the household's dynamic budget constraint and non-housing consumption. Our approach yields useful insights about several prominent foreclosure policies, but it does limit our ability to consider some others like interest rate reductions (which we do our best to consider in an appendix) or alternate mortgage designs that work through the household budget constraint. Third, because we do not model the household's budget constraint, we abstract from general equilibrium effects such as the impact of tax or debt financing needed to pay for foreclosure policies or the effect of such policies on equilibrium interest rates. Despite these limitations, our framework delivers quantitative insights regarding the mechanisms driving housing crises and offers clean economic intuitions about the relative cost-effectiveness of various policies in stemming a price-default spiral, given a particular funding scheme and level of government expenditures.

The remainder of the paper is structured as follows. Section 1 presents facts about the downturn across metropolitan areas. Section 2 introduces our basic model of the housing market, and Section 3 describes the calibration of the model. Section 4 explains and quantifies the forces at work in the national model, and Section 5 evaluates the model's ability to explain cross-sectional moments about the bust. Section 6 considers foreclosure policy, and Section 7 concludes.

²Ganong and Noel (2019b) show that essentially all default by non-investors was liquidity triggered. Bhutta et al. (2017) estimate that the median non-prime borrower does not strategically default until their equity falls to negative 74 percent. Similarly, Gerardi et al. (2017) find that there were few strategic defaulters in the PSID as most defaulters do not have the assets to make a mortgage payment and maintain their consumption. The largest estimate of the share of defaults that are strategic is 15 to 20 percent (from Experian Oliver-Wyman). See also Elul et al. (2010) and Foote et al. (2008).

Figure 2: Price and Sales in Selected MSAs With High Levels of Foreclosure



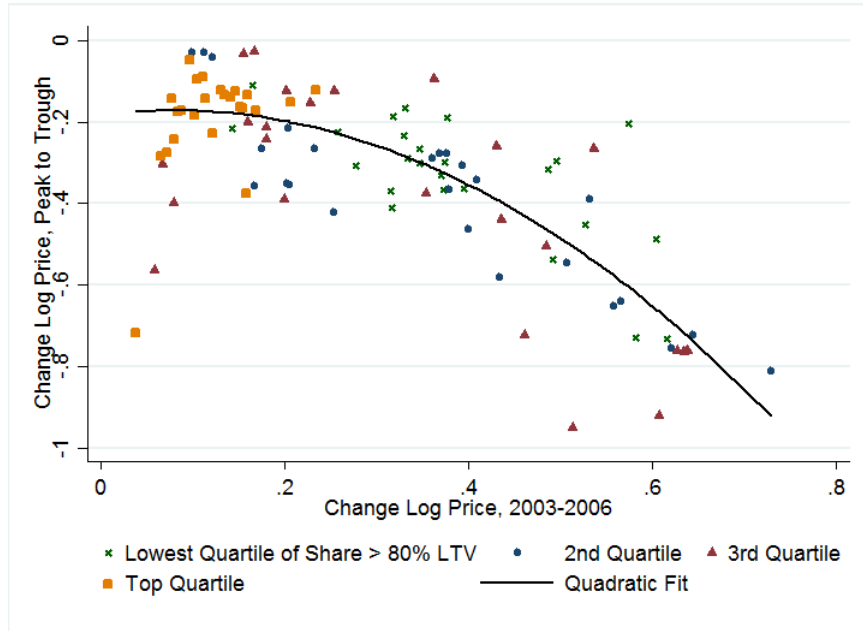
Notes: All data is seasonally adjusted CBSA-level data from CoreLogic as described in the appendix. Sales are smoothed using a moving average and normalized by the maximum monthly existing home sales, while each price index is normalized by its maximum value.

1 Empirical Facts

The national aggregate time series for price, volume, foreclosures, and REO share presented in Figure 1 mask substantial heterogeneity across metropolitan areas. To illustrate this, Figure 2 shows price and volume for four of the hardest-hit Core Based Statistical Areas (CBSAs). In Las Vegas, for instance, prices fell nearly 60 percent, and the REO share was as high as 75 percent.

To provide a more systematic analysis of the heterogeneity of the bust across cities and to motivate, calibrate, and test the model, we use a proprietary data set provided by CoreLogic supplemented by data from the United States Census. CoreLogic provides monthly data for 2000 to 2013 for the nation as a whole and 99 of the 100 largest CBSAs. The data set includes a repeat sales house price index, a house price index for non-distressed sales only, sales counts for REOs and non-distressed sales, and estimates of quantiles of the LTV distribution. We seasonally adjust the CoreLogic data and smooth the sales count series using a moving average. A complete description of the data and summary statistics are in the appendix.

Figure 3: Price Boom vs. Price Bust Across MSAs



Note: Scatter plot of seasonally adjusted data from CoreLogic along with quadratic regression line that excludes CBSAs in greater Detroit which busted without a boom. The data is described in the appendix. Each data point is an CBSA and is color coded to indicate in which quartile the CBSA falls when CBSAs are sorted by the share of homes with over 80 percent LTV in 2006. Although the highest LTV CBSAs had almost no boom and no bust (e.g. Indianapolis), the CBSAs below the best fit line tend to be MSAs with a large share of homeowners with high LTVs in 2006 (third quartile).

The best predictor of the size of the bust is the size of the preceding boom. Figure 3 plots the change in log price from 2003 to 2006 against the change in log price from each market’s peak to its trough. There is a strong downward relationship, which motivates a key feature of our model: The shock that causes the bust is a fall in home valuations that is assumed to be proportional to the size of the preceding boom.

Figure 3 also reveals a more subtle fact: Metropolitan areas that had a larger boom had a more-than-proportional larger bust. While a linear relationship between log boom size and log bust size has an r-squared of .62, adding a quadratic term that allows for larger busts in places with larger booms increases the r-squared to .68. The curvature can be seen in the best-fit line in Figure 3.³ We argue that by exacerbating the downturn in the hardest-hit areas, foreclosures explain why places with larger booms had disproportionately larger busts.

³For the best fit line, the regressions that follow, and the model calibration, we exclude two outlier CBSAs in southeast Michigan which had a large bust without a preceding boom so that the non-linearity is not overstated. All results are robust to including these two CBSAs.

This explanation has an important corollary: Because default is predominantly caused by negative equity, a larger bust should occur not only in places with a larger initial negative shock to prices, but particularly in locations with a *combination* of a large shock and a large fraction of houses with high LTVs — and thus close to default — prior to the bust. To provide suggestive evidence that this prediction is borne out in the data, the points in Figure 3 are color-coded by quartiles of share of homeowners in the CBSA with over 80 percent LTV in 2006. While the largest high LTV shares occurred in places that did not have a bust — home values were not inflated in 2006, so the denominator of LTV was lowest in these locations — one can see that the majority of CBSAs substantially below the quadratic trend line were in the upper end of the high LTV share distribution (red triangles in the figure).

To formally investigate whether the interaction of many households with high LTVs and a large preceding boom is correlated with a deep downturn, we estimate:

$$Y_i = \beta_0 + \beta_1 \Delta_{03-06} \log(P_i) + \beta_2 [\Delta_{03-06} \log(P_i)]^2 + \beta_3 X + \beta_4 (\Delta_{03-06} \log(P_i) \times X) + \varepsilon_i, \quad (1)$$

where i indexes CBSAs, X is an interacted variable, and the outcome variable Y_i is either the maximum change in log price, the maximum peak-to-trough change in log non-distressed prices, the maximum peak-to-trough REO share, or the fraction of houses that experience a foreclosure. We use two X s. First, to test whether the combination of a large bust and a large fraction of houses with high LTV creates a particularly large downturn, we use the z score of the share of mortgages with over 80 percent LTV in 2006. This regression is similar in spirit to Lamont and Stein (1999), who show that prices are more sensitive to income shocks in cities with a larger share of high-LTV households. Second, to more directly test the role of foreclosures, for price and non-distressed price we use the *ex-post* fraction of houses that experience a foreclosure. The regression results are shown in Table 1, with summary statistics and robustness checks in the appendix. With the share of mortgages with a high LTV in 2006 as the interacted variable, the fourth row of the first four columns shows the key result: The interaction term between the size of the run-up and the share of high-LTV homeowners is significantly negative for price, non-distressed price, and sales volume and significantly positive for the mean REO share of volume and the fraction of the housing stock that is foreclosed upon. This is consistent with a combination of a steep price run-up and high LTV homeowners triggering a price-default spiral.

Columns 5 and 6 show both a negative direct effect of foreclosures and a negative effect of the interaction between foreclosures and the size of the run up. While the interaction term is insignificant for the overall price index due to a large standard error, the effect is

Table 1: Cross-MSA Regressions on the Impact of the Size of the Boom and Its Interaction With High LTV Share

Dependent Variable:	$\Delta \log(P)$	$\Delta \log(P_{nd})$	Mean REO Share	% Foreclosed	$\Delta \log(P)$	$\Delta \log(P_{nd})$
X (Interacted Variable)	Z LTV > 80%	Z LTV > 80%	Z LTV > 80%	Z LTV > 80%	% Foreclosed	% Foreclosed
$\Delta \log(\text{Price})_{03-06}$	0.251 (0.414)	0.092 (0.321)	-0.531 (0.273)*	-0.362 (0.139)**	-0.662 (0.291)**	-0.758 (0.225)***
$\Delta \log(\text{Price})_{03-06}^2$	-1.886 (0.498)***	-1.537 (0.382)***	1.391 (0.331)***	0.988 (0.171)***	-0.031 (0.504)	0.355 (0.392)
X	0.054 (0.029)*	0.061 (0.024)**	-0.002 (0.021)	-0.013 (0.013)	-1.01 (0.381)***	-0.521 (0.297)*
$\Delta \log(\text{Price})_{03-06} \times X$	-0.310 (0.123)**	-0.336 (0.113)***	0.205 (0.075)***	0.235 (0.054)***	-0.631 (0.905)	-1.519 (0.711)**
r^2	0.690	0.716	0.467	0.651	0.783	0.815
N	97	97	96	96	98	98

Notes: * = 10% Significance, ** = 5% Significance, *** = 1% significance. All standard errors are robust to heteroskedasticity. Each column shows estimates of (1) with the constant suppressed. For the first four columns, the interaction variable X is the z-score for the share of houses in 2006 with an LTV over 80%. In the last two columns, the interaction variable X is the share of the housing stock that experienced a foreclosure. P_{nd} is a non-distressed only price index. The mean REO share of sales volume is the average from 2008 to 2013, and the fraction foreclosed is the fraction of the housing stock foreclosed upon over the first 8 years of the downturn. All data is from CoreLogic and described in the appendix. Data is for 98 largest CBSAs excluding Detroit MI, Warren MI in all columns, Syracuse NY in columns 1-4, and, Birmingham AL for columns 3-4. All dependent variables are peak-to-trough maximums with the exception of percentage foreclosed upon. See the appendix for robustness and regressions including southeast Michigan.

statistically significant for non-distressed prices. A negative direct effect and interaction is expected for the aggregate price index since foreclosures trade at a discount, but the negative effect on non-distressed prices provides evidence that foreclosures amplify the bust. Finally, adding the interaction with fraction foreclosed to the regression eliminates the strong and negative quadratic term on price, which suggests that the non-linearity in the size of the bust relative to the size of the boom can be accounted for by foreclosures, as will be the case in our model.

2 Model

We construct a a Diamond-Mortensen-Pissarides undirected equilibrium search model of the housing market to quantitatively analyze the effects of foreclosures and policies aimed at ameliorating their effects. Search frictions play an important role in housing markets: Houses are illiquid, most households own one house and move infrequently, buyers and sellers are largely atomistic, and search is costly, time consuming, and random.

We first describe the environment, agents, and shocks that agents receive. We then describe the housing and mortgage markets and define equilibrium.

2.1 Environment, Agents, and Shocks

Time is discrete and indexed by a t subscript, and the discount factor is β . All agents have linear utility. There are a unit mass of individuals who are assumed to be natural homeowners and a unit mass of houses which can either be owned and rented.⁴ The model is thus a closed system with a fixed population and housing stock.⁵

Individuals can be in one of four states. A mass l_t of individuals are homeowners, v_t^b are buyers who are searching for a home and renting while they do so, v_t^r are renters who do not have a foreclosure on their record but have not qualified for a mortgage and are waiting to search until they do so, and v_t^f are renting and have a foreclosure on their record. The stock of houses can have one of three statuses. l_t are owner-occupied, v_t^v are non-owner-occupied and not owned by a lender, and v_t^d are owned by lenders after a foreclosure. Of the v_t^v non-owner-occupied houses that are not owned by a lender, v_t^a are converted to rent temporarily,

⁴We focus on natural homeowners, but natural renters and transitions in and out of homeownership can be added without substantially changing the model.

⁵For tractability and to focus the paper, we abstract away from housing supply. In practice, there was little residential construction during the crisis. However, this assumption implies we may miss some features of the crisis, such as depreciation of the existing housing stock or foreclosed homes being demolished. It also means that we will not capture regional heterogeneity in housing supply elasticities when we perform our cross-city analysis.

which precludes them from being listed for sale, and v_t^n are listed for sale. As we describe below, lenders have higher holding costs, and they consequently list all of the homes they own for sale.

Homeowners experience two different shocks. First, they experience moving shocks with probability γ that represent changes in tastes and life events that induce them to leave their house as in Krainer (2001) and Ngai and Tenreyro (2014). We assume that these shocks occur at a constant rate and that only individuals who are mismatched with their house attempt to find a new one. When a moving shock occurs, what happens depends on the homeowner’s equity position. If a homeowner has negative equity, which we will define momentarily, she cannot pay off her mortgage balance with the proceeds from a sale, and consequently the homeowner is “locked in” to the current house. We assume the homeowner takes actions to accommodate the mismatch shock given her inability to move and remains a homeowner until she receives another shock.⁶ If a homeowner has positive equity, she sells her house, pays off the lender, and attempts to buy another house.

To define a homeowner’s equity position, we assume that there exists a competitive fringe of market-makers who pay homeowners a price \tilde{V}_t^n for the house and then market the home to buyers through a search and matching process described subsequently, similar to Hedlund (2016a).⁷ Homeowners thus have negative equity and are locked in if their loan balance $L > \tilde{V}_t^n$ and have positive equity and sell if $L \leq \tilde{V}_t^n$. When positive equity homeowners sell their house, they pay off their mortgage and attempt to secure pre-approval for new financing.⁸ Pre-approval occurs with equilibrium probability P_t . If the individual receives a pre-approval, she enters the housing market as a buyer. If the individual is unable to secure pre-approval, she becomes a renter and attempts to secure pre-approval again at exogenous rate γ_r . Pre-approval specifies $\Phi = (L, \mu)$, the loan amount and the interest rate at which financing can be secured at the time of purchase. We describe the endogenous pre-approval probability P_t and loan terms Φ when we introduce the mortgage market below.

The second type of shock a homeowner may receive is a liquidity shock, which occurs with time-varying probability ι_t . Again, what happens when a homeowner experiences a liquidity shock depends on her equity position. Homeowners with negative equity who experience

⁶For parsimony we do not fully model the income and savings of households. Rather, we make the reduced form assumption that underwater homeowners experience lock-in. In practice, homeowners who are only slightly underwater may have sufficient savings to make up the difference.

⁷As an alternative, one can imagine that when a homeowner enters the market, they turn into both a seller and a buyer that are independent of one another as in Ngai and Tenreyro (2014). \tilde{V}_t^n would then reflect the value of having a listing on the market, inclusive of marketing and maintenance costs.

⁸Our modeling of pre-approvals implicitly assumes that households require financing to purchase a home. In practice, few households purchase without a mortgage. Incorporating heterogeneous down payments would significantly increase model complexity while adding little economic insight.

a liquidity shock default because they are unable to afford their mortgage payments and the price they could receive from a market-maker is insufficient to pay off their mortgage. This “double trigger” default is the only source of default in our model. While “ruthless” or “strategic default” by borrowers – that is default by a homeowner with the liquidity to pay their mortgage – has occurred, there is a consensus in the literature that strategic default accounts for a very small fraction of mortgage defaults.⁹ To keep the model tractable and maintain a focus on housing market dynamics, we thus do not model strategic default, nor do we model the strategic decision of the lender to foreclose, modify the loan, rent to the foreclosed-upon homeowner, or pursue a short sale, which are options that were not widely used until late in the crisis. Consequently, we assume that homeowners with $L > \tilde{V}_t^n$ default if they experience a liquidity shock and enter the foreclosure process.

Homeowners who receive a liquidity shock who are above water, on the other hand, do not default. In our baseline model, we further assume that they can remain in their house despite the liquidity shock. In practice, homeowners with positive equity who receive a liquidity shock have various means to avoid having to sell. For example, borrowers with positive home equity could potentially borrow against it to cover temporary lost income. Homeowners with positive equity could also pursue a refinancing or a term extension. For parsimony, we do not fully model these options and instead make the reduced-form assumption that liquidity shocks do not force sales for households with positive equity. In the appendix, we consider an alternate model in which we do assume that above-water homeowners who receive liquidity shocks are forced to sell as a robustness test. This model features the same economic forces as our baseline model and does reasonably well quantitatively. However, too many households are forced to rent during the crisis relative to the data, which is why we prefer our baseline assumption.

We further assume that foreclosure occurs immediately in our baseline model. In practice, foreclosure is not immediate, and some loans in the foreclosure process do cure before they are foreclosed upon. As another robustness check, in the appendix we consider a model in which there is a delay before foreclosure completion and find similar results. We also study the effects of slowing down foreclosure completions when we analyze policy in Section 6.

Homeowners who experience a foreclosure are prevented from buying for a period of time and must rent in the interim. Foreclosure dramatically reduces a borrower’s credit score, and many lenders, the GSEs, and the FHA require buyers to wait several years after a foreclosure before they are eligible for a mortgage. Molloy and Shan (2013) use credit report data to show that households that experience a foreclosure start are 55-65 percentage points less likely to have a mortgage two years after a foreclosure start. Consequently, we assume that

⁹See references in footnote 2.

each period, individuals who defaulted become eligible to apply for a new mortgage with probability σ .

When a homeowner with positive equity sells, a market-maker takes possession of the home. As in Head (2014), each period market-makers have the option of listing a house for sale, which incurs a flow cost of m^n , or renting the house for r_t . When a homeowner with negative equity defaults and is foreclosed upon, the lender takes possession of the house and lists the house for sale, incurring a flow cost of m^d .¹⁰ Lenders do not rent out distressed properties.¹¹ We anticipate $m^d < m^n < 0$, since vacant, distressed properties tend to depreciate faster and thus require higher ongoing costs to maintain.¹² This will manifest itself in equilibrium as distressed homes selling at lower prices than other listed homes.

Buyers who have been pre-approved, renters, and households with a foreclosure on their record all rent at the equilibrium rent r_t . We assume that a given unit of housing provides rental services for ζ renter households, with $\zeta < 1$ so that renters occupy less square footage than owner-occupants as in the data. The rental market is competitive and the supply consists of those owner-occupied homes being rented out plus a permanent stock of rental homes of mass v^{rs} . The endogenous conversion of owner-occupied homes to rentals to accommodate increased rental demand during the crisis is important in the bust.

2.2 Housing Market

Buyers and sellers in the housing market are matched randomly each period according to a standard fixed-search-intensity constant-returns-to-scale matching function. Defining market tightness θ_t as to the ratio of buyers to listed homes v_t^b/v_t^s where $v_t^s = v_t^n + v_t^d$, the probability a seller meets a buyer q_t^s and the probability a buyer meets a seller q_t^b can be written as functions of θ_t . Buyers meet each type of seller in proportion to their share of listed homes in the market.

When matched, the buyer draws a valuation for the house h from a distribution $F_t(h)$

¹⁰Alternatively, we could assume that lenders also sell to market-makers and that the costs to market-makers of selling foreclosures are higher than the costs of selling non-distressed properties. Lenders would then receive a price V_t^d for the property.

¹¹We abstract away from the purchase of distressed home by institutional investors. In practice, these investors did not enter until late in the crisis (around 2012) and then only in a few markets, such as Atlanta, Tampa, and Phoenix. In our policy section we consider the impact of a government facility which purchases distressed homes and then re-introduces them into the housing market once demand rebounds, which is similar to the role played by investors.

¹²Lenders must make payments to security holders until a foreclosure liquidates, and they must also assume the costs of pursuing the foreclosure, securing, renovating, and maintaining the house, and selling the property. Even though they are paid additional fees to compensate for the costs of foreclosure and are repaid when the foreclosed property sells, the lender's effective return is far lower than its opportunity cost of capital.

which is time-varying. This valuation is a one-time utility benefit consumed at purchase and is common knowledge to both the buyer and seller. Prices are determined by generalized Nash bargaining with weight ψ for the seller. If the buyer and seller decide to transact, the seller leaves the market and the buyer obtains financing at the pre-approved terms and becomes a homeowner. If not, the buyer and seller each return to the market to be matched next period. The value of being a homeowner can be written as:

$$V_t^h(h, \Phi) = h + \Gamma_t(\Phi), \quad (2)$$

where $\Gamma_t(\Phi)$ is a continuation value function that is a function of today's loan terms Φ . This value function takes into account the possibility of moving, lock-in, and default. It is the only place where the value of being a renter both with and without a foreclosure on one's credit record enter. We relegate the formal definition of Γ_t and the value functions which are necessary to define it to the appendix.

Denote the total match surplus when a buyer pre-approved to receive a loan with terms Φ meets a seller of type $j \in \{n, d\}$ and draws a match quality h at time t by $S_t^{S,j}(h, \Phi)$, the buyer's surplus by $S_t^{B,j}(h, \Phi)$, and the seller's by $S_t^{S,j}(h, \Phi)$, with $S_t^j(h, \Phi) = S_t^{B,j}(h, \Phi) + S_t^{S,j}(h, \Phi)$. Let the price of the house if it is sold be $p_t^j(h, \Phi)$. The buyer's surplus is equal to the value of being in the house minus the down payment and the outside option of staying in the market:

$$S_t^{B,j}(h, \Phi) = V_t^h(h, \Phi) - (p_t^j(h, \Phi) - L) - \beta E_t B_{t+1}(\Phi) \quad (3)$$

where B is the value function for being a buyer. The seller's surplus is equal to the price minus the outside option of staying in the market:

$$S_t^{S,j}(h, \Phi) = p_t^j(h, \Phi) - \beta E_t \tilde{V}_{t+1}^j, \quad (4)$$

where \tilde{V}_t^j is the value of having a vacant house that can be rented or put up for sale. Because utility is linear and house valuations are purely idiosyncratic, a match results in a transaction if h is above a zero-surplus threshold denoted by $h_t^j(\Phi)$:

$$V_t^h(h_t^j(\Phi), \Phi) = -L + \beta E_t \left[B_{t+1}(\Phi) + \tilde{V}_{t+1}^j \right]. \quad (5)$$

We can then define the remaining value functions. The value of listing a house for sale as a market-marker n or as a lender d is equal to the flow payoff plus the discounted continuation value plus the expected surplus of a transaction times the probability a transaction occurs.

Because sellers who list meet buyers with probability $q^s(\theta_t)$ and transactions occur with probability $1 - F_t(h_t^j(\Phi))$, the value of putting a house up for sale as a $j = \{n, d\}$ type seller is:

$$V_t^j = m^j + \beta E_t \tilde{V}_{t+1}^j + q^s(\theta_t) \int (1 - F_t(h_t^j(\Phi))) E_t \left[S_t^{S,j}(h, \Phi) | h \geq h_t^j(\Phi) \right] dG_t^p(\Phi), \quad (6)$$

where $G_t^p(\Phi)$ is the distribution of pre-approval terms and the integral is Lebesgue. The value of a vacant home to a market maker \tilde{V}_t^n reflects the option to either list or rent the home, and in equilibrium market makers are indifferent so that:

$$\tilde{V}_t^n = r_t + \beta E_t \tilde{V}_{t+1}^n = V_t^n. \quad (7)$$

This condition pins down rents. In equilibrium, competitive market makers make zero profits in expectation, so \tilde{V}_t^n is also the price they pay households selling their home. The value of being a buyer is defined similarly to that of a seller:

$$B_t(\Phi) = -r_t + \beta E_t B_{t+1}(\Phi) + \sum_{j=n,d} q^b(\theta_t) \frac{v_t^j}{v_t^n + v_t^d} (1 - F_t(h_t^j(\Phi))) E_t \left[S_t^{B,j}(h, \Phi) | h \geq h_t^j(\Phi) \right]. \quad (8)$$

The buyer value function takes into account the possibility she can meet either normal or REO sellers.

The conditional expectation of the total surplus given that a transaction occurs can be simplified as in Ngai and Tenreyro (2014) by using (2) together with (3) and (4):

$$S_{t,}^j(h, \Phi) = V_t^h(h, \Phi) - V_t^h(h_t^j(\Phi), \Phi) = h - h_t^j(\Phi). \quad (9)$$

This implies $E_t [S_t^j | h \geq h_t^n(\Phi)] = E_t [h - h_t^n(\Phi) | h \geq h_t^n(\Phi)]$.

Prices can be backed out by using Nash bargaining along with the definitions of the surpluses (3) and (4) and (9) to obtain:

$$p_t^j(h, \Phi) = \psi (h - h_t^j(\Phi)) + \beta E_t V_{t+1}^j. \quad (10)$$

This pricing equation is intuitive. The first term contains $h - h_t^j(\Phi)$, which is a sufficient statistic for the surplus generated by the match as shown by Shimer and Werning (2007). As the seller bargaining weight ψ increases, more of the total surplus is appropriated to the seller in the form of a higher price. The final two terms represent the seller's outside option of continuing as a seller next period. These terms form the minimum price at which a sale can occur, so that all heterogeneity in prices comes from the distribution of h above the

cutoff $h_t^j(\Phi)$.

Define the joint distribution of current homeowner loan balances L and interest rates μ at time t by $G_t(L, \mu)$ and the marginal distribution of loans as $G_t(L)$. Given this specification for the housing market and the environment defined in the previous section, the laws of motion are:

$$l_{t+1} = (1 - \gamma) l_t G_t(\tilde{V}_t^n) + (1 - \iota_t) l_t \left(1 - G(\tilde{V}_t^n)\right) \quad (11)$$

$$+ v_t^b q_t^b(\theta_t) \int \sum_{j=n,d} \frac{v_t^j}{v_t^n + v_t^d} (1 - F_t(h_t^j(\Phi))) dG_t^p(\Phi)$$

$$v_{t+1}^b = \left[\gamma P_t l_t G_t(\tilde{V}_t^n) + \gamma_r P_t v_t^r + \sigma P_t v_t^f \right] \quad (12)$$

$$+ v_t^b \left[1 - q^b(\theta_t) \int \sum_{j=n,d} \frac{v_t^j}{v_t^n + v_t^d} (1 - F_t(h_t^j(\Phi))) dG_t^p(\Phi) \right]$$

$$v_{t+1}^r = (1 - \gamma_r P_t) v_t^r + \gamma (1 - P_t) l_t G_t(\tilde{V}_t^n) + \sigma (1 - P_t) v_t^f \quad (13)$$

$$v_{t+1}^v = \gamma l_t G(\tilde{V}_t^n) + v_t^n \left[1 - \int q^s(\theta_t) (1 - F_t(h_t^n(\Phi))) dG_t^p(\Phi) \right] + v_t^a \quad (14)$$

$$v_{t+1}^d = \iota_t l_t \left(1 - G(\tilde{V}_t^n)\right) + v_t^d \left[1 - \int q^s(\theta_t) (1 - F_t(h_t^d(\Phi))) dG_t^p(\Phi) \right] \quad (15)$$

$$v_{t+1}^f = (1 - \sigma) v_t^f + \iota_t l_t \left(1 - G(\tilde{V}_t^n)\right). \quad (16)$$

Equation (11) says that the stock of homeowners l_t increases due to buyers purchasing homes and decreases due to above-water homeowners receiving taste shocks and below-water homeowners receiving liquidity shocks. (12) provides the law of motion for the stock of buyers v_t^b . New potential buyers come from above-water homeowners who receive a taste shock, individuals who previously defaulted losing their foreclosure flag, and individuals who were previously denied pre-approval. Entering the market as a buyer is conditional on receiving a pre-approval, which occurs with probability P_t . (13) gives the law of motion for the stock of renters who have been denied a pre-approval. These renters re-apply for pre-approval at rate γ_r . Equation (14) gives the law of motion for houses not currently owner-occupied, which we denote as v_t^v . Because a vacant home can either be listed for sale or rented, the number of non owner-occupied homes is equal to the number of sellers last period who did not sell plus the number of homes that were rented last period plus the flow of above-water homeowners who experience a moving shock. (15) says that the mass of distressed sellers is equal to the inflow of foreclosures plus those distressed sellers who did

not sell last period. Finally, equation (16) gives the law of motion for the stock of renters v_t^f locked out of mortgage market due to a foreclosure flag on their credit report. Equilibrium in the rental market requires:

$$v_t^a + v^{rs} = \zeta \left[v_t^b + v_t^f + v_t^r \right], \quad (17)$$

where v^{rs} is the stock of dedicated rental housing. We provide the laws of motion for $G_t(L, \mu)$ and $G_t^p(\Phi)$ in the appendix.

2.3 Mortgage Market

All homeowners purchase their house with a mortgage. Mortgages in our economy can be represented by (L, μ) , a tuple that includes the loan balance L and interest rate μ . Mortgagees pay down a constant fraction of the house's principal γ_L plus interest each period as in Chatterjee and Eyigungor (2015). The required payment is thus $(\gamma_L + \mu)L$ and the principal evolves according to $L_{t+1} = (1 - \gamma_L)L_t$. To keep the model tractable, we assume that pre-payment can only occur in the event of a sale, so there is no endogenous refinancing.

Households obtain mortgages from a continuum of competitive, risk neutral lenders. We assume all lenders are identical and none go bankrupt unless the whole system becomes insolvent, so the balance sheet of the financial system can be represented by a representative lender. For tractability, we assume that at any point in time t , there is a single mortgage contract offered to borrowers. To do so, we assume that there is an institutional constraint that all mortgages are pre-approved at a fixed loan-to-value ratio ϕ relative to the average non-distressed price in the market at time t , \bar{p}_t^n .

The asset side of the representative lender's balance sheet is comprised of pre-approvals and originated mortgages. The book value Ω_t of these assets is equal to:

$$\Omega_t = l_t \int L dG_t(L) + v_t^b \int L dG_t^p(L), \quad (18)$$

where $G_t(L)$ is the marginal distribution of outstanding loan balances on originated mortgages and $G_t^p(L)$ is the marginal distribution of pre-approved loan balances. We assume that the lender raises the financing for the loan at the time of pre-approval and holds the proceeds in short-term marketable securities earning the risk-free rate μ_f until the loan is funded.

The representative lender funds itself by issuing short-term debt that is insured and thus risk-free from the perspective of its creditors. The lender is, however, subject to a regulatory

capital requirement that mandates that its book equity E_t be greater than or equal to a certain percentage χ of its assets at all times:

$$E_t \geq \chi \Omega_t. \quad (19)$$

The financial system can be in two states of the world. In the first, lenders can costlessly raise equity so that the capital constraint is satisfied. This is the default state that holds in steady state, and in this state $P_t = 1$ because the lender can serve all customers by raising equity. In the second, there is a breakdown in the equity issuance market, the ability to raise new private capital is limited, and the law of motion for lender equity is:

$$E_{t+1} = E_t + (1 - \psi) \iota_t l_t \int 1 [L_t > V_t^n] (V_t^d - L_t) dG(L_t) + \Delta_t^R, \quad (20)$$

where $G(L_t^i)$ is the distribution of loan balances at the beginning of period t . The second term represents equity losses due to default, equal to a fraction $1 - \psi$ of total book losses, with ψ reflecting the impact of government bailouts and (limited) private equity issuance.¹³ The outstanding mortgage balance is L_t , but the lender only receives V_t^d from selling a foreclosure. The final term, Δ_t^R , reflects increases in lender equity due to retained earnings. The expression for retained earnings Δ_t^R is provided in the appendix.¹⁴

The combination of capital requirements and the limited ability to issue new equity implies that lenders may be prevented from issuing enough debt to cover the full demand for new mortgage pre-approvals. In this case, for (19) to hold, Ω_t must fall, which occurs through P_t falling below one. The resulting equilibrium rationing occurs on quantity rather than price, and rationing is random. The interest rate is always set such that lenders break even in expectation. As a microfoundation, one can imagine that when households apply for financing at time t , there is random sorting into a queue. Only the first P_t fraction of applicants in the line can be serviced. Lenders and households bargain over the financing terms, with the Nash bargaining weight of the household equal to 1. This implies break-even pricing even in the rationing equilibrium.

¹³This specification seems natural, as internal and regulatory pressures to recapitalize are likely higher during periods of significant losses. This specification also puts government bailouts and private capital injections during the crisis on an equal footing, which makes economic sense and is useful when we consider policy. In Appendix D.2.4, we consider an alternative law of motion for lender equity where the private capital injection is additive rather than part of ψ . All of the the economic insights of the paper continue to hold under this alternate law of motion for lender equity, although the model fit is worse than under our preferred specification.

¹⁴We assume that the lenders believe that the probability of a breakdown in the equity issuance is sufficiently small and the benefits of debt are sufficiently large such that lenders pay out all retained earning to their shareholders and that the capital requirement binds when equity can be freely issued.

Our mortgage and banking system is similar to approaches taken by a number of recent papers that study the interaction of housing markets and the banking sector. Elenev et al. (2016) and Greenwald et al. (2018) also include capital constrained lenders in a model with default, but they focus on bank failure in a model with heterogenous lenders and tailor their model to study restructuring the GSEs and shared-appreciation mortgages, respectively. Hedlund (2016a, 2016b) and Hedlund and Garriga (2019) also include a mortgage sector in a search model of the housing market. However, their directed search model shuts down some of the main effects we highlight in our undirected search model, and their lending sector is competitive and not subject to a capital constraint. Finally, Paixao (2017) finds results of a similar magnitude in a model focused on household consumption.

2.4 Equilibrium

Given this setup we can define an equilibrium:

Definition 1. An equilibrium is defined by: masses l_t , v_t^b , v_t^n , v_t^d , v_t^v , v_t^a , v_t^r , v_t^f , value functions V_t^d , V_t^n , \tilde{V}_t^n , $V_t(h, \Phi)$, $\Gamma_t(\Phi)$, and $B_t(\Phi)$, purchase cutoffs $h_t^n(\Phi)$ and $h_t^d(\Phi)$, rents r_t and house prices $p_t^j(h, \Phi)$, a competitive interest rate μ_t , a book value of the representative lender's assets Ω_t , Equity E_t , a pre-approval probability P_t , and distributions $G_t(\Phi)$ and $G_t^p(\Phi)$ such that:

1. The laws of motion and adding up constraints (11), (12), (13), (14), (15), (16), (17), and the adding-up constraint $v_t^v = v_t^n + v_t^a$ are satisfied and the distributions $G_t(\Phi)$ and $G_t^p(\Phi)$, evolve according to the laws of motion in the appendix.
2. The value functions (2), (6) for $j = \{n, d\}$, (8), $\tilde{V}_t^n = V_t^n$, and the equation for $\Gamma_t(\Phi)$ in the appendix are satisfied.
3. The purchase cutoffs satisfy (5) for $j = \{n, d\}$.
4. Rents satisfy (7).
5. House prices satisfy (10).
6. The book value of the representative lender's assets satisfies (18). Equity satisfies (19) and, if equity issuance is limited, satisfies (20).
7. The pre-approval probability $P_t = 1$ if equity can be raised and $P_t \in [0, 1]$ satisfies (19) if equity issuance is limited.
8. Lenders break even in expectation given the interest rate.

3 Calibration

We solve our model numerically. After choosing several functional forms, we take a four-step approach to calibrating the parameters of the model. First, we externally calibrate several parameters that correspond directly to parameters commonly used in the literature or which are directly observable in the data. Second, we select several parameters to match the model’s steady state without default to pre-downturn empirical moments. Third, we calibrate parameters specific to the downturn to match the model’s simulated nationwide downturn to moments from the recent housing crisis. Finally, we evaluate our calibrated model’s ability to match cross-sectional heterogeneity in the severity of the downturn across different cities.

3.1 Parameterization of Functional Forms

We calibrate the model so that one period is a week. We use a constant-returns-to-scale Cobb-Douglas matching function so that with v_t^b buyers and v_t^s sellers there are $\Xi (v_t^b)^\xi (v_t^s)^{1-\xi}$ matches. The probability a seller meets a buyer is thus $q^s(\theta_t) = \Xi \theta_t^\xi$, and the probability a buyer meets a seller is $q^b(\theta_t) = \Xi \theta_t^{\xi-1}$. The elasticity of the matching function is set to $\xi = .84$ based on Genesove and Han (2012).¹⁵

We parameterize the distribution of idiosyncratic valuations $F(\cdot)$ as an exponential distribution with parameter λ shifted by \bar{a}_t , which represents the aggregate valuation of homes. Using an exponential is a neutral assumption because the memoryless property implies that $E_t[h - h_t^j(\Phi) | h \geq h_t^j(\Phi)] = \frac{1}{\lambda}$ for all Φ , which eliminates the effects of difficult-to-measure properties of the tail thickness of the distribution on the conditional expectation of the surplus. This assumption implies all movements in average prices $\bar{p}_t^j = \psi/\lambda + \beta E_t V_{t+1}^j$ work through V_t^j .

3.2 Externally-Calibrated Parameters

We set the annual household discount rate to five percent. Lenders and households discount at the same exogenous rate, so the riskless lender cost of capital is $\mu_f = 1/\beta - 1$. The probability of a moving shock is set to match a median tenure for owner occupants of approximately nine years from the American Housing Survey (AHS) from 1997 to 2005. We also use the AHS to set the fraction of an owner-occupied house’s floor space occupied by a renter, ζ , to be 0.65. This reflects a conservative estimate of the average fraction of square

¹⁵ Ξ is normalized to 0.5 so that the probability of matching falls on $[0, 1]$, and the results are not sensitive to this normalization.

footage per person and lot size occupied by renters who moved in the past year relative to owner occupants, as detailed in the appendix.

We set the non-distressed seller flow cost to reflect an annual maintenance cost of 3%. The Nash bargaining weight ψ is set to satisfy the Hosios condition.

We set the probability that a foreclosed-upon homeowner returns to being able to be pre-approved for a loan σ so that the average foreclosed-upon homeowner is out of the market for two-and-a-half years. Most lenders require one to seven years to pass after a foreclosure to be eligible for another mortgage. For instance, Veterans Administration loans require two years, Federal Housing Administration loans three years, and Fannie Mae and Freddie Mac required five years prior to 2011 and now require seven years, although reductions are allowed based on circumstances. We choose two-and-a-half years to fall in the middle of the range of waiting periods and alter this parameter in robustness checks.

The geometric rate of principal pay down is based on a thirty-year amortization. The LTV requirement is set to $\phi = .80$ to reflect the conforming loan limit, and our results are not sensitive to increasing this to $\phi = 0.90$. γ_r is set so that a household that is denied prepayment waits an average of eight weeks to seek another pre-approval. We set the capital requirement χ equal to 10% based on evidence from Begenau (forthcoming).¹⁶ Capital injections during the crisis $\psi = \psi_G + \psi_E$ reflect government bailouts ψ_G and limited private equity infusions. We set $\psi_G = .25$. based on evidence from Begenau et al. (2019) and let the data pin down ψ_E .¹⁷

3.3 Calibration to Steady-State Moments

We choose the initial housing preference parameter \bar{a}_0 , the shape parameter for the exponential distribution of idiosyncratic valuations λ , the dedicated stock of rental housing v^{rs} , and the REO seller flow cost m^d to match four pre-crisis moments in the data to the steady-state of the model, which we denote by dropping time subscripts. Because default was negligible pre-crisis, we consider a steady state in which $\iota = 0$, so defaults are measure zero. We also assume that in the steady-state equity issuance is costless, which implies that $P = 1$. These two assumptions simplify the steady state, as described in the appendix.

For these four parameters, we target the non-distressed seller time on the market, the average buyer time on the market, the mean house price, and the average REO discount.

¹⁶Begenau (forthcoming) estimates a Tier 1 capital requirement of 9.3%, taking into account banks' buffers over the regulatory threshold.

¹⁷Begenau et al. (2019) report total charge-offs by bank holding companies of approximately \$520 billion during the crisis. The "Paulson Plan" injected \$130 billion into these companies in the form of preferred equity (Veronesi and Zingales (2010)). While these numbers do not reflect the entire scope of losses or government interventions during the crisis, the implied bailout of 25% provides a reasonable baseline.

Table 2: Target Moments

Moment	Target	Source
Mean House Price	\$300k	Adelino et al. (2012) mean price for 10 MSAs
REO Discount	12.5%	Clauretje and Deneshvary (2009), Campbell et al. (2011)
Non-Distressed Time on Market	26.00 Weeks	Piazzesi and Schneider (2009)
Buyer Time on Market	29.05 Weeks	1.117 times seller time from Genesove and Han (2012)

Table 3: Parameter Values Calibrated to Pre-Downturn Moments

Param	Value	Units	Param	Value	Units
β	$1 - \frac{.05}{52}$	Weekly Rate	Ξ	0.5	
γ	$\frac{0.08}{52}$	Weekly Rate	ξ	0.84	
γ_L	$1/(30 \times 52)$	Weekly Rate	ζ	0.65	
γ_r	1/8	Weekly Rate	ψ	0.16	
σ	$1/(2.5 \times 52)$	Weekly Rate	m^n	-0.144	Thousands of \$
χ	0.10		ψ_G	0.25	
\bar{a}	609.67	Thousands of \$	m^d	-0.483	Thousands of \$
λ	0.015	Thousands of \$	v^{rs}	0.023	Mass (Housing stock = 1)

Intuitively, the mean price and seller time on the market are jointly determined by \bar{a}_0 and λ , the buyer time on the market relative to sellers is determined by v^{rs} , and the REO discount is determined by m^d . The REO discount in steady state is calculated as the sale price of an infinitesimal number of distressed sales in the housing market. The target values for the moments are summarized in Table 2 and detailed in the appendix, and these moments are matched exactly. Our resulting parameter values are listed in Table 3, with the parameters set exogenously in the top panel and the parameters set through moment matching in the bottom panel. Importantly, matching the REO discount implies $m^d < m^n < 0$.¹⁸

3.4 Simulating a National Housing Crisis

We simulate a housing crisis which matches the features of the national US housing market between 2006 and 2013. To do so, we start the model at its steady-state, with the exception that the initial LTV distribution matches the national loan balance distribution in 2006 from CoreLogic. We then compute the perfect foresight impulse response to a housing valuation

¹⁸Andersson and Mayock (2014) indicate that the total costs of foreclosing upon, maintaining, and selling an REO in the Great Recession were 8.5% of the house's value. In the model downturn when REO prices plunge and time on the market rises, the average REO seller's cumulative listing costs rise to 9% of the price. The m^d we use is thus of reasonable magnitude.

Table 4: Parameter Values Calibrated to Downturn Moments

Param	Value
a^{frac}	0.7525
T_E	194 Weeks
ψ_E	.390
C_l	0.328

shock and a concurrent increase in liquidity shocks. Specifically, at the time of the crisis, we hit the model with a permanent shock to home valuations, which we implement by reducing the minimum idiosyncratic valuation \bar{a}_0 to $\bar{a}_t = a^{frac}\bar{a}_0$. We use a permanent shock since it reflects a bursting bubble and is consistent with the empirical facts in Section 1. We further assume that at the time of the crisis, there is an increase in the rate of liquidity shocks ι_t , which will create default among underwater homeowners. We assume $\iota_t = C_l Unemp_t$, where C_l is a constant and $Unemp_t$ is a moving average of the time path of long-run unemployment in the Great Recession as detailed in the appendix. This assumption reflects the fact that large liquidity shocks come from persistent income shocks proxied by long-run unemployment. Finally, we assume that during the crisis lenders are limited in their ability to raise new equity capital for T_E periods. This reflects the temporary breakdown in financial markets that occurred in the Great Recession and creates a role for lender balance sheets in the crisis.

We choose four parameters that affect the downturn but not the steady state of the model to match four empirical moments of the national housing downturn. These parameters are the constant scaling the liquidity shocks C_l , the size of the decline in housing valuations a^{frac} , the fraction of losses covered by raising private capital during the crisis ψ_E , and the date T_E that equity markets fully re-open. We target four moments: The peak-to-trough decline in the housing price index, the peak-to-trough decline in non-distressed transaction volume, the average REO share between 2006 and 2013, and the total number of foreclosures between 2006 and 2013.¹⁹

To solve the model, we discretize the possible mortgage balances using an equally spaced grid with 51 grid points. Further numerical details as well as the full system of equations that result from this discretization are provided in the appendix. We do a good job matching the target moments, with no moment more than 0.2 percent from its target value. The resulting parameter values of the calibration are reported in Table 4. The 24.75 percent fall in \bar{a} implies that prices fall permanently by 11.91 percent nationally due to the valuation shock.

¹⁹The moments are jointly determined, but each moment is principally controlled by a single parameter. C_l determines the total number of foreclosures, T_E the average REO share given the number of foreclosures, a^{frac} the price decline, and ψ_E the volume decline.

3.5 Simulating the Cross-Section of Downturns

To further evaluate the performance of our model, we consider its ability to match cross-sectional variation in the severity of the crisis across metropolitan areas. To do so, we simulate a separate housing downturn in each of the 100 largest CBSAs. We assume that each CBSA is a closed system, with a housing market described by Sections 2.1 and 2.2.²⁰ We furthermore assume that there is a national representative lender. This is a good approximation to the fact that most loans are made by lenders with wide geographic coverage and most loans that are securitized are pooled geographically.²¹ This implies that the path for P_t is the same for each CBSA and is calculated from the national downturn.

We allow for cities to differ in the size of the permanent price drop, the magnitude of liquidity shocks, and the initial loan balance distribution. We focus on these three dimensions of heterogeneity because the size of the preceding price run-up is the single best predictor of the size of the ensuing downturn as described in Section 1, because cities varied dramatically in their unemployment rate in the Great Recession, and because the loan balance distribution is critical to the strength of the price-foreclosure feedback in our model. The empirical loan balance distribution comes from proprietary estimates by CoreLogic, who report quantiles of the combined loan-to-value distribution for active mortgages in 2006 computed from public records and CoreLogic’s valuation models.²² We allocate mass to finer loan balance bins in the model within each quantile equally as described in the appendix. We incorporate heterogeneity in the magnitude of liquidity shocks by letting the path of liquidity shocks in city c be $\iota_t^c = C_c Unemp_t \frac{\max Unemp^c}{\max Unemp}$, where C_c is from the national calibration, $Unemp_t$ is the national long-run unemployment time series, and $\frac{\max Unemp^c}{\max Unemp}$ is the ratio of the maximum long-run unemployment rate in city c to the national long-run unemployment rate.²³ The permanent shock to home valuations a^{frac} is chosen to generate a price decline proportional to the log price gain from 2003 to 2006:

$$\Delta \log p_{permanent} = -\eta_1 (\Delta \log p_{2003-2006} - \eta_0). \quad (21)$$

η_0 is an intercept term chosen so that $\Delta \log p_{permanent}$ matches the a^{frac} in the national

²⁰This assumption of a closed system implies that we neglect migration between CBSAs. Modeling migration between CBSAs would greatly complicate the analysis and add little in terms of insights.

²¹While one could try to model several lenders with different market shares in different cities, this would introduce tremendous complexity into the model without substantial added value.

²²Because our model concerns the entire owner-occupied housing stock and not just houses with an active mortgage, we supplement the CoreLogic data with the Census’ estimates of the fraction of owner-occupied houses with a mortgage from the 2005-2007 American Community Surveys.

²³We take this approach rather than using the time series of $Unemp^C$ directly because the BLS does not produce city-level long-run unemployment time series that are reliable at a high frequency.

calibration and η_1 is a slope term.²⁴ The limited amount of heterogeneity between cities creates a stringent test for the ability of our model to match the cross-sectional empirical patterns of the housing crisis.

η_1 is chosen to minimize the sum of squared differences between the model and the data for the peak-to-trough log aggregate price decline for each metropolitan area. We start each CBSA in the initial steady state and calculate the perfect foresight impulse response given the initial loan balance distribution, the time path of the national lender’s pre-approval probability P_t , the city-specific time path of liquidity shocks ι_t^c , and the city-specific a^{frac} calculated to satisfy (21). This yields a unique optimum of $\eta_0 = 0.113$ and $\eta_1 = 0.456$. This implies that if a city has a larger boom than the national average, roughly half of that boom relative to the national average is permanently lost when the bust hits. We return to the cross-sectional calibration in Section 5.

4 Decomposing the Effects of Foreclosures

4.1 Downturn Dynamics

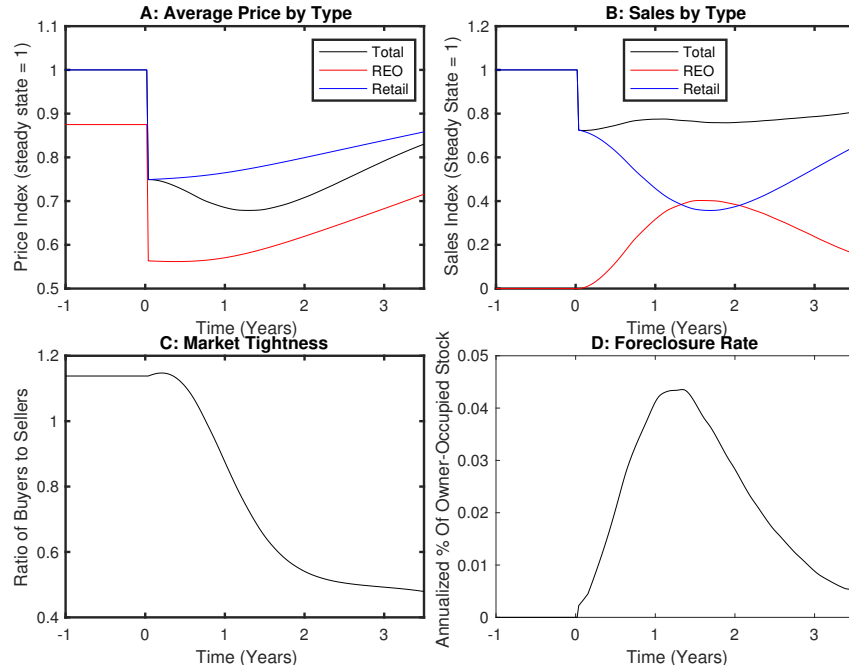
Figure 4 illustrates the model dynamics for the national downturn. As shown in panel A, at the time of the shock, prices fall considerably for both REO and non-distressed sales and gradually return to steady state as the liquidity shocks dissipate. The aggregate price index dips more than the non-distressed price index since REO sales trade at a discount. This discount widens in the crisis, consistent with evidence from Campbell et al. (2011). Panel B shows that sales fall on the impact of the shock and continue to fall substantially as REOs become prevalent in the market. Panel C shows the decline in market tightness over the crisis, and Panel D shows the dynamics of foreclosures. The largest difference between the model and the data is that the model does not feature price momentum (Guren, 2018), so prices fall immediately on the impact of the shocks rather than gradually.

4.2 Forces Affecting Prices and Sales in a Downturn

There are three main forces through which default affects the non-distressed market in our model: a lender rationing effect, a foreclosure flag effect, and a choosey buyer effect. In this subsection, we describe the intuition and qualitative impact of each effect before quantifying their respective contributions.

²⁴A handful of cities with small booms from 2003 to 2006 have a small permanent increase in their long-term price level under this formulation. Our results are not sensitive to capping $\Delta \log p_{permanent}$ at zero for these cities.

Figure 4: Dynamics of National Downturn



Note: This figure shows the results of the calibrated national model. Panels A and B show the average price and sales by type, with pre-downturn price and volume normalized to 1. Panel C shows market tightness. Panel D shows the annualized fraction of the owner occupied housing stock that is foreclosed upon at each point in time.

First, there is a foreclosure flag effect. When a homeowner defaults, the lender sells the property as an REO, but the homeowner has a foreclosure flag on her credit record and is locked out of the housing market for a time until the flag is cleared. The foreclosure process thus creates listings immediately, but the corresponding demand only arrives with a delay.

Second, there is a lender rationing effect. Default leads to declines in lender equity. Lenders ration mortgage credit because they are temporarily unable to raise equity and would violate their capital constraint if they were to fully meet the demand for new mortgages by issuing debt. Mortgage rationing causes some homeowners who sell their house to delay their next purchase because they cannot secure financing. This too creates immediate listings, but the corresponding buyers only arrive with a delay as the lenders gradually recapitalize and households re-apply for financing.²⁵

By creating an imbalance between the number of sellers and the number of buyers operating in the housing market, both the foreclosure flag and lender rationing effects reduce market tightness θ_t . The reduction in market tightness is partially offset by sellers who convert their owner-occupied house to rental space, which is required to meet the increased

²⁵See Paixao (2019) for empirical evidence that house price declines affected credit supply through bank balance sheets in the housing bust.

rental demand by foreclosed-upon households and households unable to secure financing. The fall in market tightness decreases the probability a seller meets a buyer, which in turn incentivizes sellers to transact faster, weakening their bargaining position and leading to lower prices. This incentive to sell is stronger for REO sellers who have a higher opportunity cost of not meeting a buyer, causing the REO discount to grow. Conversely, buyers are more willing to walk away from a deal, strengthening their bargaining position, which also leads to declines in price. Because the reduction in market tightness pushes down non-distressed prices, it pushes more homeowners underwater and leads to increased default, which leads to further rationing and foreclosure flag effects through a price-default spiral.

The third way that the non-distressed market is affected by default is a choosey buyer effect. Since REO sales trade at a discount, the presence of distressed sales increase the buyer's outside option to transacting, which is resampling from the distribution of sellers next period. This choosey buyer effect causes infra-marginal buyers to walk away from non-REO listings. This reduces non-distressed transaction volume and causes buyers to negotiate a lower price when they do transact. The choosey buyer effect is reinforced by the foreclosure flag effect and lender rationing effect. Both push down market tightness which has a bigger effect on the value functions of REO sellers and increases the REO discount. This in turn sweetens the prospect of being matched with an REO seller next period, amplifying the choosey buyer effect.

The choosey buyer effect is new to the literature and formalizes folk wisdom in housing markets that foreclosures empower buyers and cause them to wait for a particularly favorable transaction.²⁶ We expect that choosey buyer effects arise in other frictional asset markets with idiosyncratic valuations.

Finally, there are two other effects at work in our model that affect aggregates that are averages of the distressed and non-distressed markets. First, there is a lock-in effect. In the absence of liquidity shocks – and thus the absence of default – the permanent decline in housing valuations places some households underwater. These households are then locked

²⁶For instance, The New York Times reported that “before the recession, people simply looked for a house to buy...now they are on a quest for perfection at the perfect price,” with one real estate agent adding that “this is the fallout from all the foreclosures: buyers think that anyone who is selling must be desperate. They walk in with the bravado of, ‘The world’s coming to an end, and I want a perfect place’” (“Housing Market Slows as Buyers Get Picky” June 16, 2010). The Wall Street Journal provides similar anecdotal evidence, writing that price declines “have left many sellers unable or unwilling to lower their prices. Meanwhile, buyers remain gun shy about agreeing to any purchase without getting a deep discount. That dynamic has fueled buyers’ appetites for bank-owned foreclosures” (“Buyer’s Market? Stressed Sellers Say Not So Fast” April 25, 2011). Albrecht et al. (2007) introduce motivated sellers into a search model, but focus on steady-state matching patterns (e.g. whether a high type buyer can match with a low type seller) and asymmetric information regarding seller type. Duffie et al. (2007) consider a liquidity shock similar to our foreclosure shock, but a transaction occurs whenever an illiquid owner meets a liquid buyer, so their model does not have a choosey buyer effect.

Table 5: Decomposition of Effects in National Model

Statistic (Peak to Trough Unless Indicated)	No Liquidity Shocks	No Rationing, No Choosey Buyer	No Rationing	Full Model
Price Index	40.57%	71.49%	72.88%	100%
Non-Distressed Price Index	51.96%	74.19%	77.40%	100%
Non-Distressed Sales Volume	22.71%	51.86%	56.43%	100%
Average REO Share	0%	61.52%	62.75%	100%
Total Foreclosures	0%	76.84%	77.76%	100%

Note: Each cell indicates the fraction of the full model accounted for each column's model relative to the full model. No rationing turns off the lender rationing effect by setting $P_t = 1$. No rationing and no choosey buyer additionally turns off the choosey buyer effect by altering the buyer's value function so she does not take into account the possibility of meeting an REO seller, which leaves only the foreclosure flag effect. No default turns off all of the effects and entirely eliminates default.

into their current house until they pay down their mortgage enough to become above water. This lock-in effect has a minimal impact on prices but does lower sales volume. Second, there is a compositional effect. A greater share of REO sales makes the average sale look more like an REO, which sells faster and at a lower price both in and out of steady state. This affects sales-weighted averages such as total sales and the aggregate price index.

4.3 Quantitative Decomposition of Effects

To quantify the relative contributions of each force, we introduce them one by one. We first simulate a housing crisis in which we shut down default completely by eliminating liquidity shocks, so the only effects are the initial housing valuation shock and lock-in. We then simulate a crisis where we shut down both the lender rationing effect by assuming lenders can costlessly raise equity and the choosey buyer effect by assuming the the buyer's value function does not take into account the possibility of meeting a REO seller. This leaves only the foreclosure flag effect. We then reintroduce the choosey buyer effect but continue to shut down the lender rationing effect.

Table 5 shows the fraction of the decrease in various measures of prices, sales, and foreclosures in the full nation-wide model accounted for by each model. Our preferred measure of the extent to which foreclosures exacerbate housing downturns is the decline in non-distressed prices because it does not include compositional effects and is a direct measure of foreclosure spillovers. Table 5 reports that the model without any default account explains 51.96% of the peak-to-trough decline in non-distressed prices. The foreclosure flag effect explains an additional 22.23%, and the choosey buyer effect explains an additional 3.21%. The impact of the choosey buyer effect is significantly larger in the hardest hit CBSAs where the REO share was much higher. Finally, lender rationing explains the remaining 22.60%. Note that

lender rationing plays a particularly large role in explaining the decline in sales volume. Indeed, to jointly match the substantial price and volume declines in the data, our model requires a significant lender rationing channel. Overall, our quantitative results suggest that accounting for default is crucial to understanding the dynamics of the housing bust.

These effects are substantially larger than the spillover effects of foreclosures estimated by microeconomic studies that cannot account for the general equilibrium effects of foreclosure at the search market level or the effects of foreclosures on lender balance sheets (e.g. Campbell et al., 2011; Gerardi et al., 2015; Anenberg and Kung, 2014). An exception is Mian et al. (2014), who find much larger effects using more macro variation arising from differences in foreclosure policies at state lines, which is consistent with our finding of a substantial search-market-level effect.

4.4 Robustness

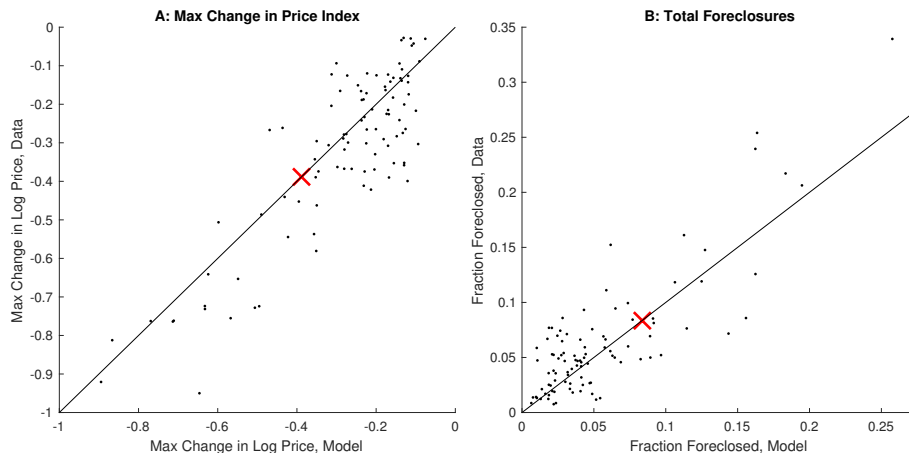
In the appendix we present calibration robustness checks to show that our results are robust to some of our assumed parameter values, in particular γ_r , σ , and ζ . There is some dispersion in the strength of the various effects across calibrations, but generally the lender rationing effect accounts for between 20 and 25 percent of the overall decline in non-distressed prices, the choosey buyer effect accounts for approximately three percent, and the foreclosure flag effect accounts for 20 to 25 percent of the decline. In all cases, there are important spillovers from foreclosures to the non-distressed market, principally through the foreclosure flag and lender rationing channels.

The appendix also reports results for four alternate models. First, we show that a model without the lender rationing fails to account for the decline in sales in the data. Second, we show that a model in which there is some foreclosure delay can still fit the data quite well. Third, we show that a model in which positive-equity homeowners who experience an liquidity shock are forced to sell does reasonably well matching the cross-section but overstates the amount of conversion to rental relative to the data. Finally, we show that we obtain similar results with an alternate parameterization for private equity injections.

5 Cross-City Quantitative Analysis

To provide further support for our structural model and calibration, we now assess whether our model with a limited amount of heterogeneity can account for differences in the downturn across cities. We then illustrate the importance of default and foreclosure in explaining the downturn by showing that our model does a better job at matching the cross-sectional

Figure 5: Cross-CBSA Simulations vs. Data



Note: Each panel shows scatter plots of data vs simulation results for 96 CBSAs in regression analysis. The red X represents the national simulation and each black dot is a CBSA. The 45-degree line illustrates a perfect match between the model and the data. The variable being plotted shown in each plot’s title. The data is described in the appendix. The calibration methodology, which fits the cross-cities model only to the aggregate price decline in panel A, is described in text. The price decline is the maximum peak-to-trough change, while the fraction foreclosed which is the total from 2006 to 2013.

moments described in Section 1 than a model without default.

5.1 Cross-Sectional Model Fit

Figure 5 plots our simulated results from the baseline model against actual data for 96 CBSAs (black dots) and the national model (red X). Panel A shows the maximum log change in aggregate prices, which is used in the calibration of η_1 . The model fits well, with the data points clustering around the 45-degree line across the spectrum of price declines. Indeed, when we regress the simulated data on the actual data we get a coefficient of 1.005, and we cannot statistically reject a coefficient of one and an intercept of zero. Panel B shows the fraction of the housing stock foreclosed upon over eight years. This is a moment used in the national calibration, so the national model is fits almost exactly, but it is not a target for the cross-section. Nonetheless, when we regress the simulated data on the real data, we get a coefficient of .992 and we cannot reject a coefficient of one and an intercept of zero. The limited heterogeneity in our model thus does a good job capturing the variation in default across cities.²⁷

²⁷The appendix presents a calibration where we do not include heterogeneity in the liquidity shock series by CBSA. The model qualitatively has fits many of the features described in this section but does not quantitatively fit quite as well: if we regress the log change in the aggregate price index in the model on the corresponding data, we get an r-squared of 0.667 rather than 0.736. The model fits better with the unemployment heterogeneity because of a few hard-hit CBSAs like Las Vegas.

Table 6: Cross-CBSA Simulations vs. Data

Variable	$\Delta \log P$	$\Delta \log (P_{nd})$	Mean REO	%	%
			Share	Foreclose	Convert
Reg Coef of	1.005	1.389	0.8283	0.992	0.434
Data on Model	(0.063)	(0.087)	(0.090)	(0.069)	(0.055)
R^2	0.736	0.734	0.482	0.695	0.419

Note: Each column shows a comparison of the model and data for the given variable. The comparisons show the slope term of a regression of the actual data on the model simulated data. Standard errors are in parenthesis.

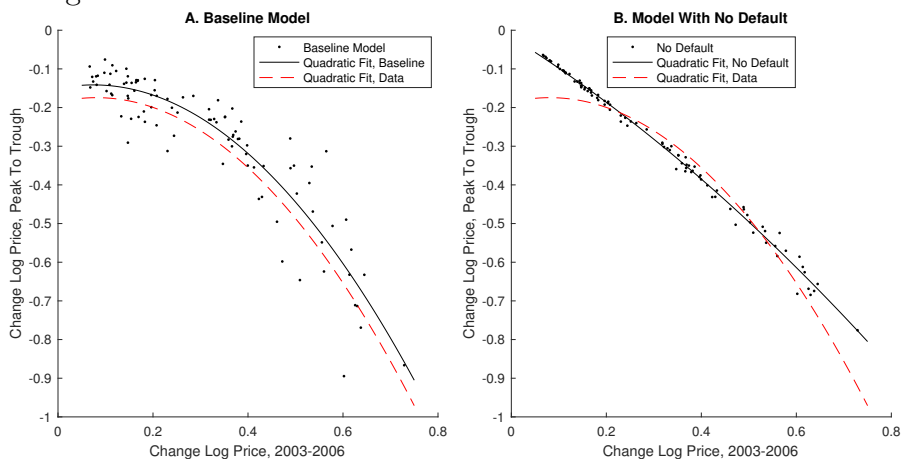
Table 6 summarizes the model fit for the national prices and foreclosures as well as three other metrics: the decline in non-distressed prices, the mean REO share, and a proxy for the share of the owner-occupied housing stock converted to rentals. For each outcome, we report the coefficient and r-squared we obtain when we regress the simulated data on the actual data. The coefficient is somewhat too high for non-distressed prices because the model under-predicts the decline in non-distressed prices in the hardest hit CBSAs. However, the non-distressed price index in these CBSAs indicates a declining foreclosure discount, which is inconsistent with the literature and suggests that these indices are biased downward by negative quality selection on the non-distressed houses that sell in the hardest-hit CSBAs. The model does well with REO share, although the coefficient is a bit too low because the model under-predicts the sales decline in the least-hit CBSAs. In the data, even cities with no price decline exhibited a significant volume decline. The volume decline from the decrease in national pre-approvals is not enough to fully match the volume decline in these cities.

The last column provides an additional out-of-sample test by comparing the maximum share of owner-occupied homes converted to rental homes in the model to approximate figures for 2006 to 2013 described in the appendix. This is important because if the model dramatically under-predicts the number of conversions, the change in market tightness in the bust will be too strong and the model will ascribe too much of the downturn to foreclosures. The model predicts that at the peak level of conversion, 7.38 percent of the owner-occupied housing stock is converted to rentals nationally relative to 4.35 percent in the data. Across cities, there is a positive correlation between the model and the data despite a considerable amount of noise due to the data we use for conversion being a crude proxy. The amount of endogenous conversion in our model is thus of the right order of magnitude.

5.2 Comparison With No Default Model

We now ask how well our model can account for cross-sectional variation in the data relative to a model with no default. To do so, we compare our model to a model with no liquidity

Figure 6: Boom vs. Bust in Baseline and No Default Models



Note: The left panel shows the size of the boom vs. the model simulated data for the baseline calibrated model with default, while the right panel shows the same plot for the no default model. The black solid line is a best quadratic fit. The red dashed line shows the best quadratic fit to the actual data. For the no default model, $\eta_1 = 0.844$.

shocks and thus no default or foreclosures. We calibrate the model to match the national price decline and optimally choose η_1 using equation (21) as before to give the no-default model the best possible opportunity to match the data.

Figure 6 replicates Figure 3 and plots the size of the bust against the size of the boom using model simulations for the baseline and no default models rather than the raw data. The solid black line shows the best quadratic fit to the model simulated data, while the red dashed line shows the best quadratic fit to the actual data as in Figure 3.

The baseline model quantitatively captures the non-log-linearity in the size of the bust relative to the size of the boom in the data: The solid black and dashed red lines are close to each other and have similar curvature. Furthermore, moving from a linear fit to a quadratic fit in the simulated data increases the r-squared from 0.78 to 0.85, relative to 0.62 to 0.68 in the actual data. By contrast, the model without default is nearly linear in the size of the bust relative to the size of the boom and adding a quadratic term does little to improve the fit, with the r-squared rising from 0.990 to only 0.994. This is because essentially all of the price decline comes from the permanent decrease in prices that is proportional to the boom. Consequently, the model fit for price is much better in both the hardest and least hardest hit areas in the model with default relative to the model without default. A final measure of fit is the mean squared error for the aggregate price index. Without default, the mean squared error is 0.0166, while with default this falls to 0.0135.

To further explore the improvement in fit, Table 7 reports the interaction term from regression (1) from Table 1 using simulated outcomes from the baseline and no default

Table 7: Model vs. Data: Interaction of Size of Boom With High LTV Share

$\Delta \log(P) \times Z_{LTV > 80\%}$	$\Delta \log(P)$	$\Delta \log(P_{nd})$	Mean REO Share	% Foreclosed
Baseline	-0.396 (.034)***	-0.140 (0.013)***	0.307 (0.029)***	0.167 (.014)***
No Default	-.102 (.004)***	-.102 (.004)***	0	0
Data	-0.310 (0.123)**	-0.336 (0.113)***	0.205 (0.075)***	0.235 (0.054)***

Notes: * = 10% Significance, ** = 5% Significance *** = 1% significance. All standard errors are robust to heteroskedasticity. Each column shows estimates of (1) with the constant suppressed. P_{nd} is a non-distressed only price index. The mean REO share of sales volume is the average from 2008 to 2012, and the fraction foreclosed is the fraction of the housing stock foreclosed upon over the first 8 years of the downturn. All data is from CoreLogic and described in the appendix.

models. The model does qualitatively well. The no default model has a negative interaction for price due to lock in, but the coefficient is too small relative to the data. The baseline model with default, by contrast, does a better job of matching the data, although the interaction is a too strong for regular prices and too weak for non-distressed prices.

Overall, we conclude that including default is crucial for models to match cross-sectional moments from the recent housing bust.

6 Foreclosure Policy

A number of foreclosure mitigation policies have been proposed to reduce the severity of a housing crisis. In this section, we use our calibrated model to perform a quantitative study of the positive effects of several different interventions, focusing on their effects on house prices declines and foreclosure rates. We begin by evaluating the effects of interventions at the local level, that is in one city holding national credit conditions fixed, and then move on to evaluating the effects of national government policy interventions that allow credit conditions to be endogenous.

Before examining the policies, there are some important limitations to our policy analysis that the reader should keep in mind. First, since we do not fully model household consumption and the household costs of default, we are unable to make quantitative statements about welfare.²⁸ Second, while we compute the dollar costs to the government of various types of

²⁸In practice, default and foreclosure can have significant welfare effects that are outside the scope of our model. For example, defaulting is costly for households. Foreclosures have significant non-pecuniary costs and lead to worse outcomes for children (Diamond et al., 2019), , adversely affect future employment outcomes (Brevoort and Cooper, 2013) and carry a significant cost of social stigma (Guiso et al., 2013). Furthermore, default and foreclosure amplify price declines in our model, and these declines in housing

policy interventions, we do not model the means by which the government finances the expenditure, which may involve distortionary taxation or borrowing that affects equilibrium interest rates. Nonetheless, we are able to give clear intuitions on the positive effects of various government interventions and make clear, quantitative statements about the cost-effectiveness of various types of foreclosure policies in terms of mitigating a price-default spiral.

6.1 Limiting Foreclosure Completions

We begin our policy analysis by considering the impact of slowing down the rate of foreclosure completions, which was a policy intervention hotly debated during the housing crisis. Proponents argued that this policy could be implemented quickly and at a low cost relative to other government interventions. However, this policy also had its detractors. For example, during the 2012 Presidential campaign, Mitt Romney proposed removing legal barriers to foreclosure completion to get the economic damage over with rather than slowing them down to prolong things.

Since most of the variation in foreclosure timelines is at the the state or municipal level, we consider the local impact of slowing down the rate of foreclosure in a single city, taking national lender balance sheets as given. That is, we hold P_t fixed for this policy only. To incorporate the policy into our model, we continue to assume that homeowners becomes delinquent at the rate ι_t . However, we now further assume that a maximum Φ of the housing stock can be foreclosed upon each week due to institutional or legal constraints. In particular, we set Φ to half of the maximum rate of foreclosure completions in the baseline model, which corresponds to limiting the total number of foreclosures to 2.20% of the total local housing stock in a given year.²⁹

Limiting foreclosure completions results in an equilibrium backlog of foreclosure starts waiting to be completed during the crisis. We assume that homeowners in the backlog are randomly processed. Finally, due to the lag, homeowners who are delinquent but who have not been foreclosed upon have the opportunity to “cure” out of foreclosure by becoming current on their loan, which we assume occurs to underwater homeowners each period with probability ω . This allows us to evaluate how the effectiveness of the policy depends on the rate at which homeowners recover from a liquidity shock such as a long-term unemployment

prices can have their own welfare impacts by impeding borrowing by households and firms (Iacoviello, 2005; Chaney et al., 2012; Adelino et al. 2015) and through aggregate demand effects (Mian and Sufi, 2011; Mian and Sufi, 2014).

²⁹Note that capping the total number of foreclosure completions allowed in a given period is just one way to implement a slowing down policy. Alternatively, one could simply assume that foreclosure completions occur at some rate σ_f . We have explored this policy and find similar qualitative and quantitative results.

Table 8: Effects of Limiting Foreclosure Completions

ω	$\Delta \log P_{agg}$	$\Delta \log P_{nd}$	Total Foreclosures
Baseline (No Policy)	-0.388	-0.289	8.37%
0	-0.363	-0.301	9.24%
$1/(3 \times 52)$	-0.339	-0.281	7.38%
$1/(2 \times 52)$	-0.335	-0.278	7.05%
$1/(1 \times 52)$	-0.329	-0.273	6.53%

Notes: The table shows the peak-to-trough decline in log aggregate prices, log non-distressed prices, and the total foreclosures from 2006 to 2013 under each policy. All policies are for a local intervention that does not affect the representative lender's balance sheet.

spell. Homeowners also cure if prices rise to the point that they have positive equity, in which case they can sell their house.

Our results are reported in Table 8. We first consider the case in which homeowners never cure from their liquidity shock, so $\omega = 0$. In this case, slowing down foreclosures is actually mildly *counterproductive*. While there is a 6.44% smaller decline in the aggregate price index, this is purely a compositional effect, and the non-distressed price index actually falls by 4.15% *more*.

To understand why slowing down foreclosures makes non-distressed price declines larger, recall that the non-distressed average price \bar{p}_t^n is a constant markup over the seller's value function V_t^n . By equation (6), the seller's value function is equivalent to holding a financial perpetuity which costs m^n each period but pays out θ/λ each period with time-varying probability equal to the probability that a seller transacts with a buyer. A policy of slowing down foreclosures leads to two competing forces on the value of this claim. First, in any given period, the policy reduces the imbalance between the number of buyers and sellers, leading to a smaller peak-to-trough decline in the equilibrium probability of a seller transacting. However, the policy also delays the recovery, so that the decline in the seller's probability of sale lasts longer. In our baseline calibration, the latter effect weakly dominates, leading to lower prices, and ultimately more default. Because of the lengthened crisis, few homeowners cure by coming above water. The relative strength of these two forces is a numerical result and depends on our calibration.³⁰

When homeowners exogenously cure ($\omega > 0$), slowing down the pace of foreclosures can reduce the severity of the crisis if ω is high enough because since some homeowners recover before they are foreclosed upon, leading to a smaller price-default spiral. Quantitatively, if $\omega = 1/(2 * 52)$ so that homeowners cure on average after two years, halving the maximum flow of foreclosures reduces the non-distressed price decline by 3.81%. If $\omega = 1/52$, the same

³⁰For example, if sellers discount the future by more, then the first effect can dominate.

policy reduces the non-distressed price decline by 5.54%. Given the evidence of long-term scarring for displaced workers in the labor literature, ω is likely low in practice. However, our results suggest that if policy makers expect a quick recovery either in the labor market or in house prices, slowing down foreclosures may be modestly effective.

6.2 Government Cash or Equity Injections

We now turn our attention to three policy interventions implemented at the national level which can affect lender balance sheets and once again let the pre-approval probability P_t be endogenous.

The first policy we consider is an additional government equity injection into the financial sector. Our baseline calibration has such an intervention already built into it to reflect the 25% bailout of lenders losses during the crisis by the Federal government. We begin our analysis by considering the impact of larger government bailouts of financial institutions. Specifically, we consider the impact of cash injections equal to 30%, 40%, and 50% of bank losses

The results from this policy experiment are reported in the first three rows of Table 9. The baseline calibration with a cash injection of 25% of banking sector losses leads to a non-distressed price index log decline of -0.289 and a foreclosure rate of 8.34%. The present-value cost to the government is \$1,584, calculated on a per household basis.³¹ ³² A 30% injection of cash as a percentage of losses results in a 10.67% smaller non-distressed price decline and a 8.39% reduction in the number of foreclosures and costs \$1,619 per household. A 40% injection of cash as a percentage of losses results in a 20.52% smaller non-distressed price decline and a 17.07% reduction in the number of foreclosures and costs \$1,819 per household. A 50% injection of cash as a percentage of losses results in a 23.88% smaller price decline and a 19.30% reduction in foreclosures. It costs \$2,175 per household.

Additional government bailouts of the financial sector ameliorate the impact of the housing crisis by increasing lender equity and thus reducing the amount by which the representative lender has to ration pre-approvals, a force which accounts for 22.6 percent of the decline in non-distressed prices. This reduced rationing has a direct effect on market tightness and drives up non-distressed prices, which brings some households above water, reduces default, and undoes some of the price-default spiral. The effect of additional equity injections is strong because the 10% capital requirement implies that for each 1% increase in

³¹Formulae for the cost to the government of each policy can be found in the appendix.

³²These figures reflect the cost of a cash bailout. A better policy is likely to purchase preferred stock. Since the lender does not default along the perfect foresight equilibrium path, this constitutes a riskless investment on the part of the government.

Table 9: National Policy Interventions

Policy	$\Delta \log P_{nd}$	Total Foreclosures	Per-Household Cost
Baseline (25% Bailout)	-0.289	8.34%	\$1,584
30% Bailout	-0.258	7.64%	\$1,619
40% Bailout	-0.230	6.92%	\$1,819
50% Bailout	-0.220	6.73%	\$2,175
25% Bailout, \$5K Principal Reduction	-0.272	7.59%	\$1,782
25% Bailout, \$10K Principal Reduction	-0.259	6.98%	\$1,917
25% Bailout, $\sigma_g = 1/52$	-0.159	4.98%	\$2,150

Notes: The table shows the peak-to-trough decline in log non-distressed prices, the total foreclosures from 2006 to 2013, and per-household costs to the government. The intervention is a national intervention that affects the representative lender's balance sheet. The policy is as indicated, and formulae for computing the per-household cost are in the appendix.

bank equity, the bank can increase the size of the balance sheet by 10%.³³

6.3 Mortgage Modification

The next policy we consider is principal reduction, which was implemented as part of the Home Affordable Modification (HAMP) PRA program. This program financed principal forgiveness for homeowners, with the principal reduction capped at the point where the LTV ratio reached 115%. Using a regression discontinuity design, Ganong and Noel (2019a) document that, controlling for payment reduction, HAMP principal reductions for underwater homeowners had no effect on the short-run incidence of default. Scharlemann and Shore (2016) report similar results using a regression kink design.

To keep our analysis in line with the actual HAMP program, which only reduced principal up to the point where LTV ratios reached 115%, we consider a policy which offers principal forgiveness of Φ dollars or until 115% LTV is reached (whichever is less) to all homeowners with LTV ratios exceeding 115% at the onset of the crisis. We assume that the government pays the residual principal and interest payments to the bank throughout the life of the loan, so the bank does not incur any losses on its balance sheet. To isolate the impact of the principal reduction, we assume that incidence of the liquidity shocks remains constant. Finally, we again consider this policy as incremental, taking the baseline 25% lender bailout as given.

The quantitative results for principal reduction are in the fourth and fifth rows of Table 9. Relative to a baseline with no principal reduction, \$5,000 principal reduction up to a 115% LTV cap lowers the price decline by 5.83% and the incidence of foreclosure by 9.04%

³³Note that higher levels of private equity injections during the crisis would have similar effects.

and has a total cost of \$1,782 per household. \$10,000 principal reduction up to a 115% LTV cap lowers the price decline by 10.47% and the incidence of default by 16.35% and has a total cost of \$1,917 per household.

The first result to note about principal reduction is that it can be effective at mitigating price declines and foreclosures. At first blush, this may seem to contradict to micro-econometric studies like Ganong and Noel (2019a) and Scharlemann and Shore (2016) who find that HAMP principal forgiveness had no effect on default at the margin. However, if we were to compare underwater households who receive principal reduction to those who do not in our model, we would also find no difference in short-run default rates, since the policy does not bring households above water. Our model is thus entirely consistent with their micro findings.

The effectiveness of principal reductions is instead due to two equilibrium effects that are absorbed into a constant or fixed effect in micro-econometric studies. First, the policy affects default in the future because more households are above water than otherwise would be as prices rise. As agents are forward-looking, the reduction in future default feeds back into a smaller price decline at the start of the crisis. Second, principal reductions act as an indirect bailout to lenders, as households that receive a liquidity shock and default have a smaller principal balance than they otherwise would have. Our equilibrium model suggests that micro studies on the impact of principal forgiveness like Ganong and Noel (2019a) and Scharlemann and Shore (2016) may understate the full impact of programs like HAMP because they cannot account for the equilibrium impacts of the policy.

The second result to note about principal reduction is that it is less cost effective than the other policies we consider, as shown in Table 9. This is because principal forgiveness is imperfectly targeted. Intuitively, the government cannot tell who will receive a liquidity shock in the future and thus gives principal reduction to all households with sufficiently high LTV, which drives up the cost of the policy relative to a policy that targets households conditional on default. The other two policies are better-targeted because they condition on default: Equity injections cover a fraction of lender losses due to default, and government purchases of distressed homes only occur in the event of a foreclosure. These policies thus do not spend money to mitigate foreclosures that may not occur, while principal reduction does.

6.4 Government Purchase of Distressed Houses

The final policy intervention we consider is a government facility to purchase distressed homes and then slowly re-introduce them to the market. In our model, foreclosures create listings

today but potential buyers are locked out of the market, which puts downward pressure on prices. Slowing down the rate at which foreclosed properties are listed on the market for sale could address this dynamic imbalance between supply and demand and lead to smaller price declines and less default. This does not occur in equilibrium because competitive lenders do not internalize the fact that by listing a property today they are creating more foreclosures and lowering the price they can command for a foreclosure. This externality creates scope for government intervention.

We implement such an intervention within our model by assuming that the government sets up a facility to purchase distressed homes at the price of V_t^d so that lenders are indifferent between listing the property for sale and selling it to the government. The government then re-introduces REOs into the market at the rate σ_g . While the house is off the market, the government pays per-period costs of m^d while keeping the home off the market, which makes sense because as with lenders selling a foreclosure, the fact that the house is vacant implies increased depreciation and thus higher maintenance costs. When a house is re-introduced by the government back into the market at time T , the government sells the house to a market-maker at a price V_T^d .

Our results are reported in the final row of table Table 9. The policy is highly effective: A rate of $\sigma_g = 1/52$, corresponding to keeping the house off the market for an average of 1 year, leads to a 44.8% smaller national price decline and a 40.3% reduction in the number of foreclosures. The total cost to the government is \$2,150 per household. By contrast, Table 9 shows that a 50% lender bailout costs the government \$2,175 per household but delivers significantly smaller reductions in default and non-distressed prices. The policy is thus quite cost-effective, even accounting for the government's high maintenance costs when they hold homes off the market.

The reason this policy intervention is highly effective is that it mitigates both the foreclosure flag *and* lender rationing channels discussed in Section 4.³⁴ It clearly mitigates the foreclosure flag effect by directly addressing the dynamic imbalance of demand and supply created by the foreclosure process, as described above. The lender rationing channel is also weakened because of the interaction between the foreclosure flag and lender rationing effects: By weakening the foreclosure flag effect, there is less default and smaller bank losses, which then mitigates the credit rationing by banks. The total result is significantly less amplification during the crisis and a far smaller price-default spiral.

³⁴Recall that, even in the absence of any lender rationing, the foreclosure flag effect itself accounts for 22.2% of the total price decline.

7 Conclusion

This paper uses a structural analysis to show that foreclosures have important equilibrium effects that exacerbate housing downturns and to analyze foreclosure mitigation policy. We develop a quantitative search model of the housing market in which default erodes lender balance sheets, lenders sell foreclosed homes at a discount due to high holding costs, and homeowners who are foreclosed upon cannot immediately purchase another home. Lender rationing and the impact of foreclosure flags on potential buyers' credit records reduce the number of buyers relative to sellers, worsening seller outside options. Sellers, and particularly REO sellers, become highly motivated to sell, while buyers become more choosy due to the presence of distressed REO sellers offering properties at a discount. These effects create downward pressure on non-distressed prices, which in turn leads to additional default and a price-default spiral.

In our quantitative analysis, these equilibrium effects prove crucial to match the empirically observed declines in house prices and transaction volumes during the housing crisis. Furthermore, the model with default is better able to match the non-linearity in boom size relative to bust size across cities relative to a model without default. The deterioration in lender balance sheets generates a decline in non-distressed prices of 22.6 percent, while the foreclosure flag and choosy buyer effects cause an additional 25.4 percent decline.

The presence of sizable equilibrium effects of foreclosures opens the door to for foreclosure mitigation policy to ameliorate a downturn, and we use our quantitative model to compare several policies. The most cost effective policy we consider is a government intervention that holds foreclosures off the market until demand rebounds, thereby rectifying the dynamic imbalance of supply and demand caused by foreclosures. Lender equity injections are also quite effective. The least cost effective policy is principal reduction as implemented by HAMP, although it is more effective than a partial-equilibrium analysis would suggest since it acts as a poorly-targeted bailout of lenders. Finally, slowing down foreclosures can be counterproductive if households do not cure out of foreclosure quickly enough because it lengthens the crisis, which offsets the benefits of having fewer foreclosures on the market at any one time. However, this policy can be effective if the cure rate is sufficiently fast.

Overall, our findings suggest that models of the housing market need to incorporate features that allow for default to cause overshooting in a bust. Our findings also imply that foreclosures and some foreclosure policies have far stronger effects than those implied by micro studies that absorb the equilibrium effects into a constant or fixed effects. We hope future work continues to refine our understanding of the equilibrium effects of foreclosures and their role in shaping foreclosure policy.

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