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Consumption in the Great Recession: The Financial Distress Channel*

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Abstract

During the Great Recession, the collapse of consumption across the U.S. varied greatly but systematically with house-price declines. We find that financial distress among U.S. households amplified the sensitivity of consumption to house-price shocks. We uncover two essential facts: (1) the decline in house prices led to an increase in household financial distress prior to the decline in income during the recession, and (2) at the zip-code level, the prevalence of financial distress prior to the recession was positively correlated with house-price declines at the onset of the recession. Using a rich-estimated-dynamic model to measure the financial distress channel, we find that these two facts amplify the aggregate drop in consumption by 7 percent and 45 percent respectively.

Keywords: Consumption, Credit Card, Mortgage, Bankruptcy, Foreclosure, Delinquency, Financial Distress, Great Recession.
JEL Classification: D31, D58, E21, E44, G11, G12, G21.

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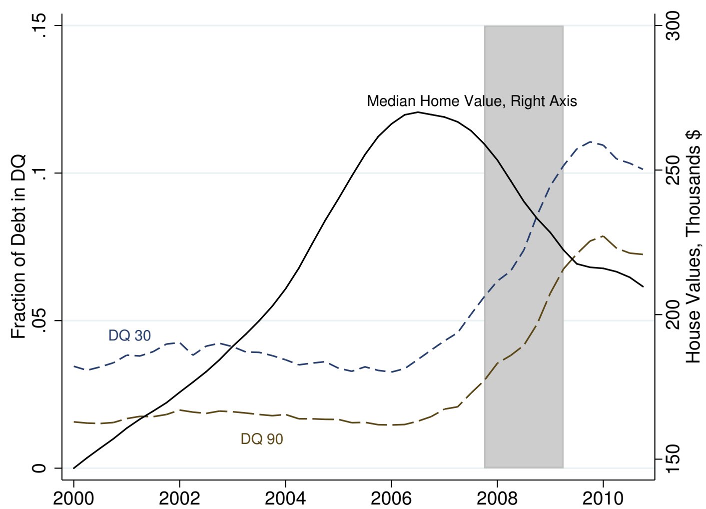
1 Introduction

A substantial proportion of US households experience *financial distress* (FD): they are either unable to repay a debt as initially promised, have mostly exhausted the options to borrow quickly, or both. This paper's goal is to show that FD matters for macroeconomics, and in particular, for the severe reduction in consumption seen in the Great Recession.

A definitive feature of the Great Recession was the large decline in house prices that occurred before the recession actually began (solid line in Figure 1). As a matter of accounting, this decline immediately damaged household balance sheets. Moreover, importantly for the argument we make, as a matter household liquidity and solvency, this decline increased the prevalence of FD before the beginning of the recession (dashed lines in Figure 1). This provides the first of two channels through which FD amplified the decline of aggregate consumption during the recession.

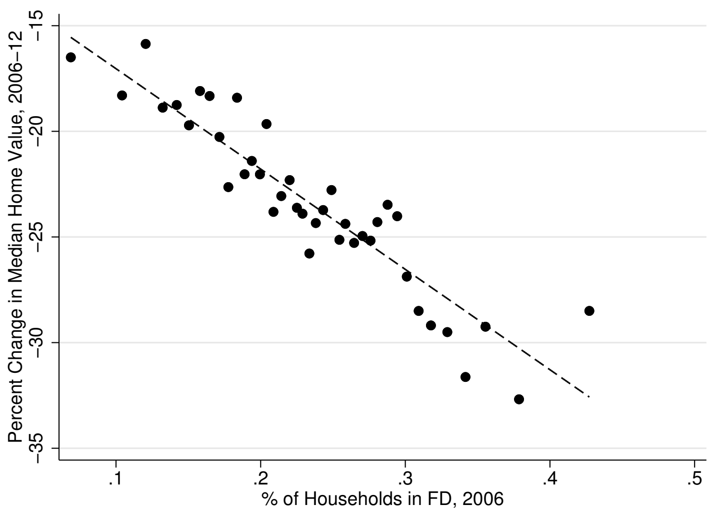
Figure 1: Evolution of Aggregate House Prices and Financial Distress



Note: The shaded area represents the recession. DQ 30 and 90 here respectively specify the fraction of debt that is at least 30 days delinquent and 90 days delinquent.

The second channel by which FD matters for aggregate outcomes comes from the novel fact we establish: using zip-code-level data, we show that during the Great Recession there was a positive covariance between housing wealth shocks and the incidence of "initial" FD. Figure 2 shows that regions with larger FD in 2006 faced a larger decline in house prices during 2006-12.

Figure 2: Regional Changes in House Prices by Financial Distress



Note: FD is measured with CL80, which is the share of individuals who used 80% or more of their credit credit limit at some point in a given year. For ease of viewing, the data have been divided into 40 bins with respect to CL80, and each dot represents the mean of that bin weighted by the number of households in each zip code as of 2006.

The two channels we uncover do not by themselves establish the claim we made: that FD matters for macroeconomic dynamics. This requires a model, as the state of being in FD is a choice. The second contribution of the paper is to provide a framework in which FD as an endogenous object matters for consumption dynamics. We develop a model of consumption rich enough to encompass heterogeneity in income risk, life-cycle consumption needs, housing, debt repayment, and, importantly, nonrepayment and formal default (bankruptcy). We then use our model to demonstrate the channels at work and, critically, show via counterfactuals how they determine the response of aggregate consumption. Our conclusion is that FD amplified the drop in aggregate consumption by up to 45 percent.

A key reason for this finding is that in the model individuals in FD tend to have higher marginal propensities to consume (MPC) out of housing shocks. We corroborate this model-based implication by merging data on car registrations with our dataset on FD. Indeed, we find that areas with higher FD experienced larger consumption reductions in response to exogenous house price shocks, even controlling for regional differences in income, net wealth, and-critically-housing leverage.[1] Overall, our results suggest the Great Recession was a bit of a perfect storm: not only did it increase the share of people in FD (who tend to be more responsive), it also disproportionately afflicted individuals in FD (because of the positive covariance between FD and housing shocks).

While our focus is only on consumption, that interest is driven by the standard (Old and New Keynesian) view that at high frequencies, what happens to consumption is important for the determination of income. Our model helps us contribute to an understanding of income movements in the sense that it allows for an empirically accurate distribution of FD across geographies to play a role in determining consumption dynamics in more aggregated (zip-code-level) outcomes. Under our maintained view of short-run output determination, this yields insight into the steep fall in income or output during the period following the housing price collapse.

On one level, FD resembles conventional measures of liquidity constraints. As we show, one definition defines FD in just this way. Measures of indebtedness are also plausibly natural contributors to FD: given any fixed borrowing capacity, more debt means less ability to handle the next shock that arrives. Similarly, by limiting access to collateral, high leverage hinders access to future credit. It was shown in the seminal work of Mian, Rao, and Sufi [2013], and surveyed in Mian and Sufi [2010], that those who had borrowed heavily against their homes lost most or all of their wealth as house prices fell. In the Great Recession, the attendant sudden reduction in credit access is plausibly linked to the large drop in aggregate consumption–and later linked to output and employment as well. As we will argue, FD is broader than either, especially when it is defined to include information encoded in past debt repayment decisions, something done neither by current debt nor leverage. This is because of the presence of costs associated with formal and informal debt default (e.g., "stigma," collections efforts, reduced future credit access, administrative fees), whereby those in FD face the risk of having to choose between not repaying debt and lowering consumption.

[1] Of course, the differences in FD across regions are almost certainly not exogenous. There are unobserved differences across households in FD and households that are not in FD. In our model, that heterogeneity is captured by discount-factor heterogeneity as in Athreya, Mustre-del Río, and Sánchez [2019].

Two formal definitions of FD are those developed in Athreya, Mustre-del Río, and Sánchez [2019] and follow the logic laid out at the outset. The first is having debts past due, and the second is having exhausted a large fraction of available credit–as measured by credit card utilization rates. In that work, both these measures of FD are shown to be relatively common (i.e., high incidence) but also disproportionately accounted for by a smaller group of households persistently in FD. Thus, the empirics of FD in the U.S. suggest that individual consumption dynamics over longer-run periods are affected for many, with some facing much more frequent difficulties.

Financial distress–defined as we have done–offers an encompassing, easily measured, and timely way to gauge the vulnerability of households and the economy at large to shocks. Encompassing, because unlike other measures, it does not require knowledge of the items on households' balance sheets, nor of prices that are needed to compute measures such as net worth or leverage. For example, one may well have little measured wealth but substantial amounts of poorly measured wealth (e.g., cash in a mattress or, more often, assets with uncertain liquidation values) or access to supplementary credit from hard-to-view sources (e.g., family or business assets that can be liquidated). Similarly, individuals with low levels of observable net worth may not be constrained.[2] By contrast, seeing an individual become significantly delinquent, or utilizing most if not all unsecured credit, is far more telling. It is unlikely, given the costs associated with being delinquent or utilizing typically expensive unsecured credit, that there are hidden sources of cheap credit available or that the household seeks to increase its net worth position in preparation for retirement, and so on. More importantly, since the marginal cost of credit is what determines the marginal propensity to consume (MPC), and the latter is central to accounts of macroeconomic susceptibility to shocks, FD is a window into both individual and aggregate MPCs. As for its ease of measurement and timeliness, our measures of FD are built on rich (individual-level) and frequently updated credit bureau data, precisely what Athreya, Mustre-del Río, and Sánchez [2019] exploit.

[2]Think of those in middle age who are beginning wealth accumulation for retirement. At the other end of the spectrum, those with high observable wealth or net worth may be significantly constrained due to debt and other potentially more informal future obligations not easily seen.

1.1 Related literature

In addition to the work cited above, on which we build most closely, our work is tied to several recent papers. First, Patterson [2018] documents that individuals with higher marginal propensities to consume out of income shocks are also those whose earnings are cyclically more sensitive. She shows that this positive covariance is large enough to increase shock amplification by 40 percent over a benchmark in which all workers are equally exposed. Our paper complements hers by focusing on marginal propensities to consume out of housing wealth shocks and documenting that the covariance between these shocks and financial distress amplifies housing shocks. Second, Herkenhoff and Ohanian [2012], Herkenhoff [2013], and Auclert and Mitman [2019] demonstrate that the ability of households to default on debt changes macroeconomic dynamics. While Herkenhoff and Ohanian [2012] and Herkenhoff [2013] emphasize the importance of default for the dynamics of unemployment, Auclert and Mitman [2019] consider the Keynesian channels of aggregate demand (via sticky prices and the attendant AD externalities à la Blanchard and Kiyotaki [1987]). Campbell and Cocco [2007], Aladangady [2017], and Aruoba, Elul, and Kalemli-Ozcan [2018] use individual-level data to investigate the consumption response to a change in house prices. Campbell and Cocco [2007] focus on the differences between the life cycle and homeownership. Aladangady [2017] and Aruoba, Elul, and Kalemli-Ozcan [2018] obtain empirical results in line with our finding that greater FD is associated with higher MPCs. Those papers use zip-code-level data to highlight the importance of household financial constraints in shaping consumption responses. We connect these findings to FD, emphasize the importance of the geographical distribution of FD and house price shocks, and use a life-cycle model to compute counterfactual exercises. Lastly, our finding on the positive covariance between initial FD and subsequent house price declines at the zip-code level is related to Piazzesi and Schneider [2016]. They document that during the 2000s cheaper houses experienced a stronger boom-bust cycle than more expensive ones using city-level data from Zillow. Consistent with their fact, we find that zip-codes with higher initial FD, and subsequently larger house price depreciations, also tend to have cheaper homes in 2006.

There are several papers analyzing the decline in consumption after house price shocks or, more generally, during the recession. Berger, Guerrieri, Lorenzoni, and Vavra [2018] was the first paper to study how prices affect consumption in a heterogeneous agent model with incomplete markets.

They show how consumption responses depend on factors like the level and distribution of debt, the size and history of house price shocks, and the level of credit supply. Kaplan, Mitman, and Violante [2019] build a quantitative model with long-term mortgages and default to study which are the necessary shocks to account for the joint evolution of house prices and consumption during the recession. Their key new component is the change in expected house price growth. Finally, Garriga and Hedlund [2017] use a model of housing search to show that an endogenous decline in housing liquidity amplifies the decline in consumption during the Great Recession.

The remainder of the paper is structured as follows. In Section 2, we lay out the key facts related to the geographic variation in FD in the U.S.–as of 2006. We then show empirically how this map contains predictive power for the observed variation in the size of house price shocks. With those facts established, we turn in Section 3 to our model, which as stated above, is very rich and hence capable of incorporating the desired margins of adjustment–and the costs associated with those adjustments. Section 4 presents the parameterization. Section 5 contains the results, and Section 6 offers concluding remarks.

2 FD and the Great Recession

This paper will make use of two main definitions of FD developed by Athreya, Mustre-del Río, and Sánchez [2019]. The first of these, labeled DQ30, gives the percentage of people who are at least 30 days delinquent on a credit card payment at some point during the year. The second measure, which we label CL80, is defined as the percentage of people within a zip code who have reached at least 80% of their credit limit over the same time interval.[3] We demonstrate now that under either of our measures, FD varied substantially across geographies before the Great Recession, was correlated with housing net worth shocks, and influenced a household's reaction–in terms of consumption spending–to these shocks.

[3]A more complete definition of these and other definitions of FD used in this paper are available in appendix section A.1.4.

2.1 Geographic Dispersion in FD by Zip Codes

FD, as we have defined it, provides a useful and timely indicator of the financial health of a zip code that is easily accessible (in our case, via Equifax data). Figure 3 shows that both of our measures across zip codes convey the same message: the incidence of FD varied widely, even relatively regionally, in 2006, were highest in the Deep South and some coastal areas, and lower in the upper Midwest and Great Plains.[4] Indeed, no state can be characterized as having entirely high or low FD. What is more, these national pictures mask a high degree of dispersion in individual cities. Take, for example, two contiguous zip codes in St. Louis, Missouri: 63110 to the east and 63105 to the west. In 2006, 5.8% of households in the west were in FD (here, by the 30-day delinquent standard) on a credit card payment, while the incidence was almost triple that in the east, at 16.1%. When housing prices collapsed starting in 2006, the west lost an average $31,123 of the value of their homes, which is less than half of the average loss that occurred in our sample. And though the east lost even less, just $22,386 on average, this hides disproportionate loss. Taking the home value loss as a percentage of net wealth, however, the west lost just .4% while the east lost a full 6.6%.

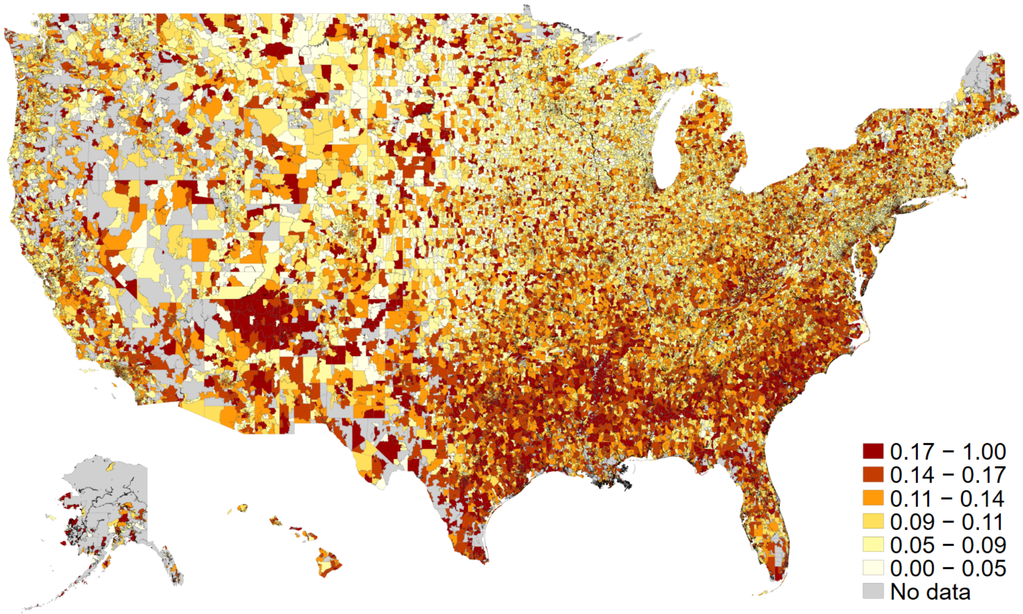
Clearly, then, the experiences of these two adjacent zip codes were very different in terms of FD and wealth loss. This case is not an anomaly. In our sample, the standard deviation of FD (here using DQ30) across counties is .034, but the average standard deviation of FD across zip codes within a county is roughly twice as high: a full .060. Similarly, while the standard deviation of FD by the CL80 standard across counties is .036, the average standard deviation among zip codes in the same county is again twice as high, .073. Thus, aggregate statistics mask substantial heterogeneity in FD prevailing in more disaggregated data.

The second fact we emphasize about the geography of FD is that as of the eve of the Great Recession, the indcidence of FD exhibits a substantial positive covariance with the size of the eventual fall in house prices. This will be detailed in section 2.2.

The data displayed so far are, of course, purely cross-sectional. Does such a snapshot convey the general state of consumers' health and sensitivity to shocks, especially over time? The answer depends on the persistence of FD. Here, we emphasize a main finding of Athreya, Mustre-del Río, and Sánchez

[4] This fact is not unique to 2006; similar maps from other years up to the present day reveal the same.

(a) DQ30



(b) CL80

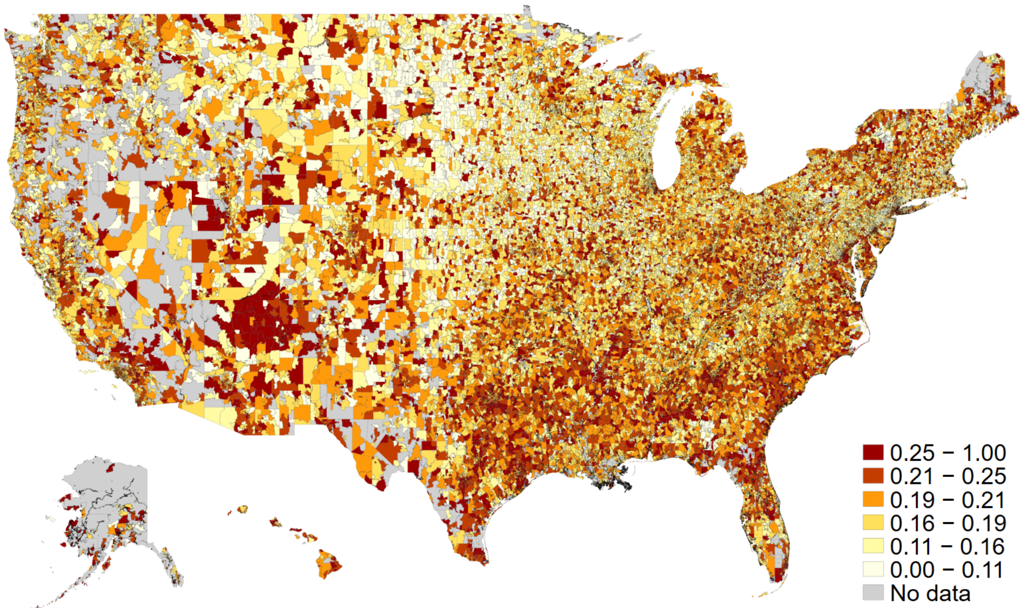


Figure 3: National Maps of FD Dispersion in 2006
Source: FRBNY Consumer Credit Panel/Equifax.

[2019], who showed, using data at the individual level, that FD is remarkably persistent under similar measures. For example, conditional on being in FD today, an individual is roughly four times more likely to be in FD two years from now as compared to the average person. Thinking, then, of a zip code as a collection of such individuals, these measures provide a relatively stable indicator of FD characteristics across time.

The foregoing supports our focus on cross-sectional measures across granular geographies. As we noted above, variation in outcomes across zip codes is substantial. Table 1 summarizes the characteristics of zip codes by the incidence of FD. Perhaps naturally, FD is inversely related to a variety of other measures of economic health, wealth, and human capital.

Areas with high FD tended in 2006 to have lower incomes, net wealth, and home values. Their lower wealth prevents them from sustaining higher levels of debt, both in terms of housing debt and, perhaps more surprisingly, credit card debt. This arises because despite using a higher proportion of their available credit, zip codes with high FD also tend on average to have significantly lower credit limits. On the other side, zip codes with low FD enjoy the double bonus of having both a high credit limit and having used a lower portion of that limit. Clearly, then, from an ex-ante perspective, the latter is better situated to weather financial losses. In terms of human capital, people in the highest FD quintile are less than half as likely to have earned a high school diploma as those in the zip code drawn from the lowest FD quintile.

The preceding is highly suggestive of the connection between FD and broader financial health at the local level. Nonetheless, given that the probability of a person being in FD declines dramatically over the life cycle,[5] it might be worried that we are merely picking up differences in age across zip codes. There is indeed some of this effect, but the difference in mean age between the top and bottom quintile is just slightly over two years. Second, the work of Mian, Rao, and Sufi [2013] is important to acknowledge here. Their findings might suggest that in looking at FD, we are merely repackaging leverage. An important part of our empirics is that this is *not* what is happening. We see from Table 1 that there is no consistent relationship between housing leverage and FD. If anything, housing leverage seems to be *decreasing* in FD. This is displayed more explicitly in Figure 4.

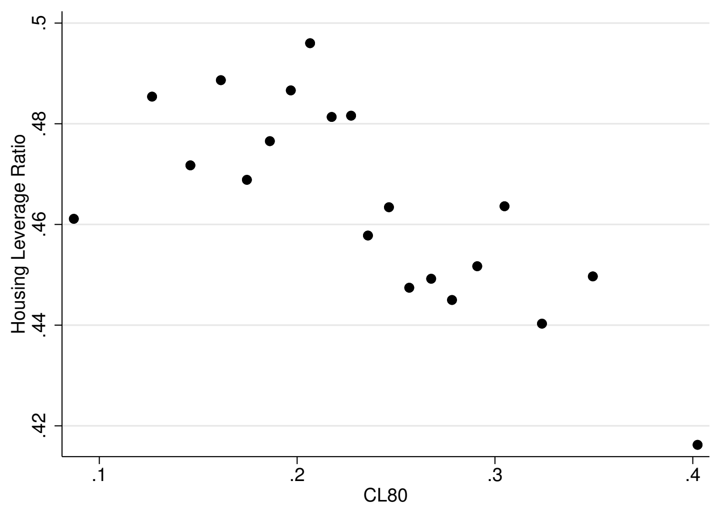
[5] Athreya, Mustre-del Río, and Sánchez [2019] document that the percentage of people in FD declines by over 40% from age 25 until age 55.

Table 1: Descriptive Statistics by Quintile of FD, 2006

	Quintiles of CL80				
	1	2	3	4	5
			Wealth		
Income Per Household $000	108.1	85.84	71.52	62.66	55.51
Net Wealth Per Household $000	990.9	704.4	488.3	382.9	285.5
Median Home Value $000	388.7	334.1	296.8	258.8	236.1
			Human Capital		
Less Than HS	9.540	12.35	14.91	16.51	18.13
HS	21.54	24.03	25.70	27.37	29.00
College	68.92	63.62	59.38	56.13	52.87
Age	45.01	44.37	43.82	43.64	43.29
			Debt and Delinquency		
% that Own a Home	0.717	0.677	0.652	0.644	0.628
% with Housing Debt	0.502	0.455	0.424	0.397	0.369
Housing Debt per Home Owner $000	208.5	176.8	156.2	132.8	118.5
CC Debt Per Household $000	5.100	4.851	4.494	4.323	4.094
Housing Leverage	0.475	0.481	0.474	0.450	0.443
CL80	0.126	0.186	0.227	0.270	0.342
% with Housing Debt and FD	0.097	0.145	0.179	0.226	0.294

Note: Here "housing" debt refers to a mortgage or home equity line of credit. Housing leverage is then measured as housing debt divided by the total housing wealth in each geography. All means are weighted by the number of households, save housing debt per homeowner, which naturally is weighted by homeowners. "% with Housing Debt and FD" gives the percentage of those with housing debt who are also in FD under the CL80 criterion.

Figure 4: Correlation of Housing Leverage with FD (CL80) in 2006



Note: Housing leverage is here measured as housing debt (including mortgages and home equity lines of credit) divided by the total housing wealth in each geography. For ease of viewing, the data have been divided into 20 bins with respect to CL80, and each dot represents the mean of that bin weighted by the number of households in each zip code as of 2006.

Finally, given that we intend to look at the interaction between FD and housing shocks, it may be worried that the differences in FD across zip codes are driven mainly by people who do not own homes, especially because those in high FD zip codes are somewhat less likely to own the home in which they live. To examine this, we identify within the Equifax data whether someone owns a home by whether they have either a mortgage or a home equity line of credit. Of course, this method does not allow us to identify homeowners who have completely paid off their homes and have no home equity lines of credit. The "% with Housing Debt" row is included to show the extent of this omission and reveals that our proxy for homeownership in Equifax usually underestimates the percentage of households that own the home they live in by about a third. This is in line with estimates of the percentage of homeowners who have paid off their mortgages.

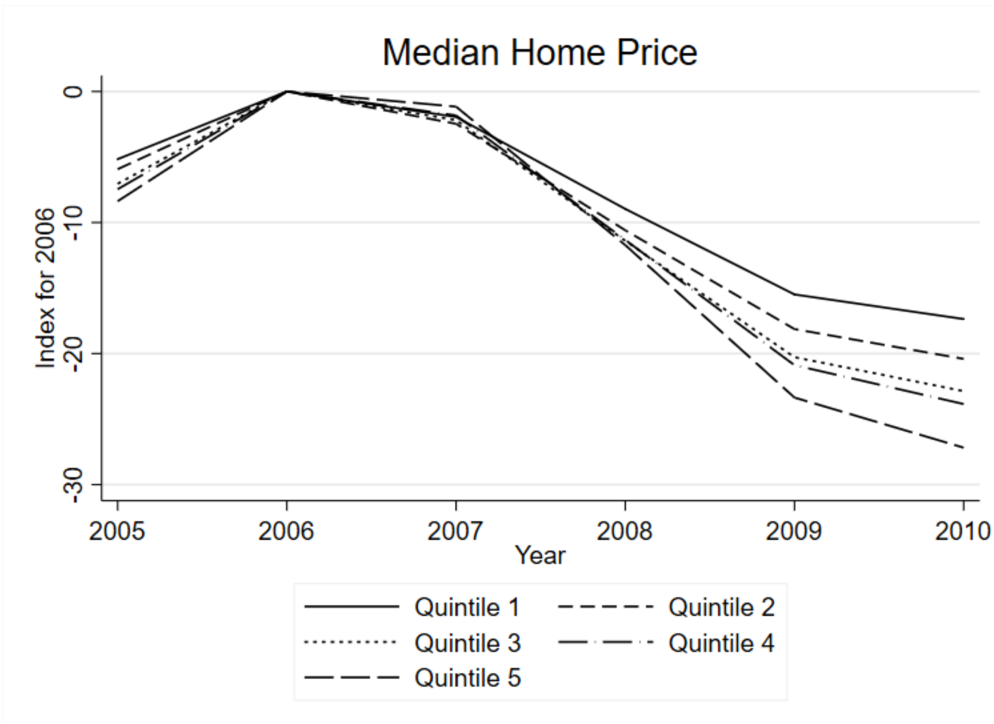
The last line of the table then shows that when we consider the fraction of people identified in this way to both own a home and be in FD, the resulting differences between quintiles are similar in magnitude to those of FD considered directly. What is more, the omission of homeowners who do not have housing debt leads this final row to be an underestimate. Adding a third to the bottom row, which would be the approximate bias if homeowners without housing debt had the same distribution of FD as homeowners with housing debt, exceeds the difference between that and the unconditional percentage in FD for every quintile. Thus, it is highly unlikely that our results are being driven by people who do not own homes.

2.2 The Relationship between Housing Shocks and Financial Distress

A central feature of the Great Recession was the unprecedented size and geographic scope of declines in house prices. Figure 5 exemplifies this dynamic. Each line plots the evolution of median home prices at the zip code level grouped by quintile of financial distress. The lines suggest that by 2009, regardless of FD, median home prices declined on average by 20% relative to their 2006 levels. However, these lines also show a fairly systematic relationship between FD in 2006 and subsequent home price declines: zip codes with higher FD in 2006 experienced large median home price declines.

In considering the implications of this drop in house prices for household balance sheets, it is useful to convey the lost housing wealth as a frac-

Figure 5: Evolution of House Prices by Quintiles of FD

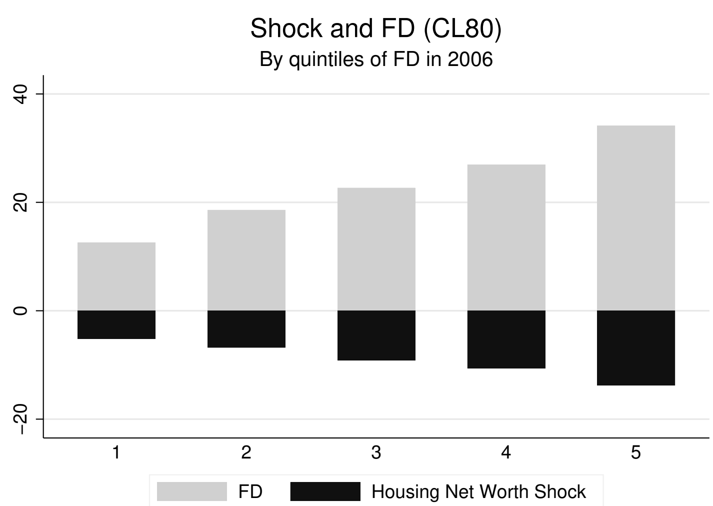


Note: Weighted by owner-occupied housing units at the zip code level.

tion of net wealth. We follow Mian, Rao, and Sufi [2013] in defining net wealth NW as the sum of housing wealth H and financial wealth FW less debt D. In their framework, the housing net worth shock is then defined as ${}^{\Delta log(p^{H,i}_{06-09})H^i_{06}}/{}_{NW^i_{06}}$ using an appropriate housing price index $p^{H,i}$. Our methodology for constructing these and other variables at the zip code and county levels is thoroughly described in appendix section A.1.

Figure 6 documents the major fact to be established in this section: the incidence of the housing wealth shock upon zip codes was highly positively correlated with household FD. That is, higher FD in 2006 was associated with larger declines in housing wealth shocks in the ensuing three years of significant recession. This fact is robust to numerous other measurements of FD, including DQ30 and CL80 conditional on homeownership. Appendix section A.2 shows the associated graphs for those cases.

Figure 6: Housing Wealth Shocks (2006-09) and FD (CL80) in 2006



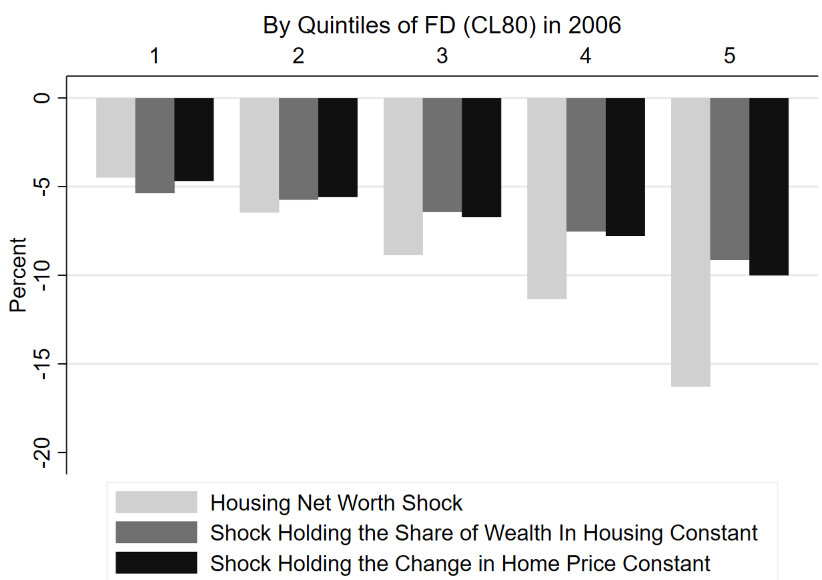
Sources: IRS SOI, CoreLogic HPI, FRBNY Consumer Credit Panel/Equifax, Census Bureau. "FD" quintile means are weighted by the number of households in each zip code as of 2006, and "housing net worth shock" quintile means are weighted by 2006 net wealth.

To understand what is driving this correlation, consider the following decomposition: we can separate the housing net wealth shock into two component parts, the change in home prices and the share of wealth that was held in housing in 2006. We rewrite the shock definition as

$$\frac{\Delta log(p^{H,i}_{06-09})H^i_{06}}{NW^i_{06}} = \underbrace{\left(\frac{\Delta log(p^{H,i}_{06-09})H^i_{06}}{H^i_{06}}\right)}_{\text{chg. in house prices}} \underbrace{\left(\frac{H^i_{06}}{NW^i_{06}}\right)}_{\text{share of wealth in housing}}$$

Setting each component in turn at its sample mean to isolate variation in the other, we uncover the relative importance of each component to the overall housing net worth shock. Figure 7 plots the resulting relationship and shows that the effects of each are meaningfully correlated with FD. In other words, the observed relationship between housing price shocks during the Great Recession and FD would have existed regardless of whether changes in home prices or the share of wealth people held in their homes were held fixed across the country. This again points to a sort of "double whammy" borne by communities with high levels of FD: they held a higher portion of household wealth in their homes and faced steeper price losses on those homes.

Figure 7: Decomposition of 2006-09 House Price Shock



Sources: IRS SOI, CoreLogic HPI, FRBNY Consumer Credit Panel/Equifax, Census Bureau. Group means are weighted by net wealth in each zip code as of 2006.

In sum, the results from this section reveal that the Great Recession was novel from the point of view of FD both because of the high incidence of distress, but also, and perhaps more importantly, because of the positive correlation between FD prior to the recession and subsequent house price declines. Importantly, we show this positive correlation is not a simple artifact of a third variable (e.g., housing leverage), but rather a peculiarity of the U.S. economy at the onset of the Great Recession. Central to our main thesis is how financial distress affects the pass-through of housing shocks into consumption? Relatedly, how important was the documented relationship between financial distress and house price shocks in determining this pass-through? Since the latter question is a counterfactual exercise it requires a fully specified model to which we turn next.

3 A Dynamic Model of Financial Distress

The results from the previous section show that prior to the Great Recession the U.S. economy was characterized by an elevated level of financial distress, which was nonuniformly distributed across regions in the country. More interestingly, the decline in house prices that precipitated the Great Recession was also nonuniformly distributed across the U.S.; it was more severe in regions with higher initial FD. Because financial distress is an endogenous choice, a model is required to fully answer the question at hand, which is how FD affected the transmission of housing shocks into consumption. In this section, we present such a model. In the subsequent sections, we use this model as a laboratory to assess the role played by financial distress in the response of consumption to housing shocks and quantifying the importance of the positive correlation between initial distress and house price shocks.

3.1 Benchmark Model

There is a continuum of finitely lived individuals who are risk-averse and discount the future exponentially. All individuals survive to the next period with probability ρ_n, which depends on age n. Each agent works for a finite number of periods and then retires at age W. Agents are subject to idiosyncratic risk to their income y (which will be specified below). Each period, agents choose non-durable consumption c, housing h, and financial assets (or debt) a'. Lastly, the model allows for preference heterogeneity of a restricted form: individuals will differ in how they discount the future. Specifically, a share p_L of the population has a discount factor of β_L, while the remaining share has a discount factor of $\beta_H \geq \beta_L$. The distribution of discount factors will be estimated to be consistent with select household balance sheet facts, following Athreya, Mustre-del Río, and Sánchez [2019]. We next detail the agent's choices in the asset and real estate markets.

Agents enter each period either as nonhomeowners or homeowners. Rental houses are of size h_R, while owner-occupied houses vary in discrete sizes $h' \in \{h_1, h_2, \ldots, h_H\}$. To finance the purchase of nonrental houses, agents borrow using mortgages b'. Importantly, borrowing capacity in the mortgage market is endogenously given by a zero-profit condition on lenders due to limited commitment of agents' ability to repay mortgages (as detailed below).

If agents choose to save ($a > 0$) in the financial asset a, they are paid a risk-free rate r. However, when agents borrow ($a \leq 0$), the price of their debt q also depends on their borrowing, because debt may be repudiated and lenders must break even. Debt repudiation can occur in one of two ways. First, the agent may simply cease payment. This is known as delinquency (DQ) or informal default. With delinquency, a households debt is not necessarily forgiven, however. Instead, debts are forgiven with probability η. The probabilistic elimination of debts is meant to capture the presence of creditors periodically giving up on collections efforts. With probability 1-η, then, a households rolled-over debt is not discharged, and, in this case, the household pays a penalty rate, r_R, of interest higher than the average rate paid by borrowers. Moreover, in any period of delinquency, we prohibit saving, and since the agent did not borrow but in fact failed to repay as promised, their consumption equals income. Second, as is standard in models of unsecured debt, agents may invoke formal default via a procedure that represents consumer bankruptcy (BK). If this is the path chosen, all debts are erased, and in the period of filing for bankruptcy, consumption equals income net of the monetary cost f of filing for bankruptcy.

To better understand the structure of the model, Figures 8 and 9 provide a simple visual description of the choices faced by agents who enter a period as nonhomeowners or homeowners, respectively.

Figure 8: Decision tree of a nonhomeowner

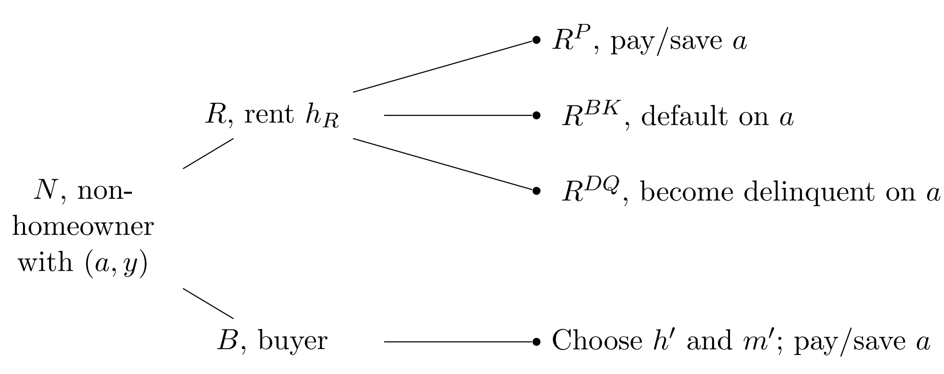
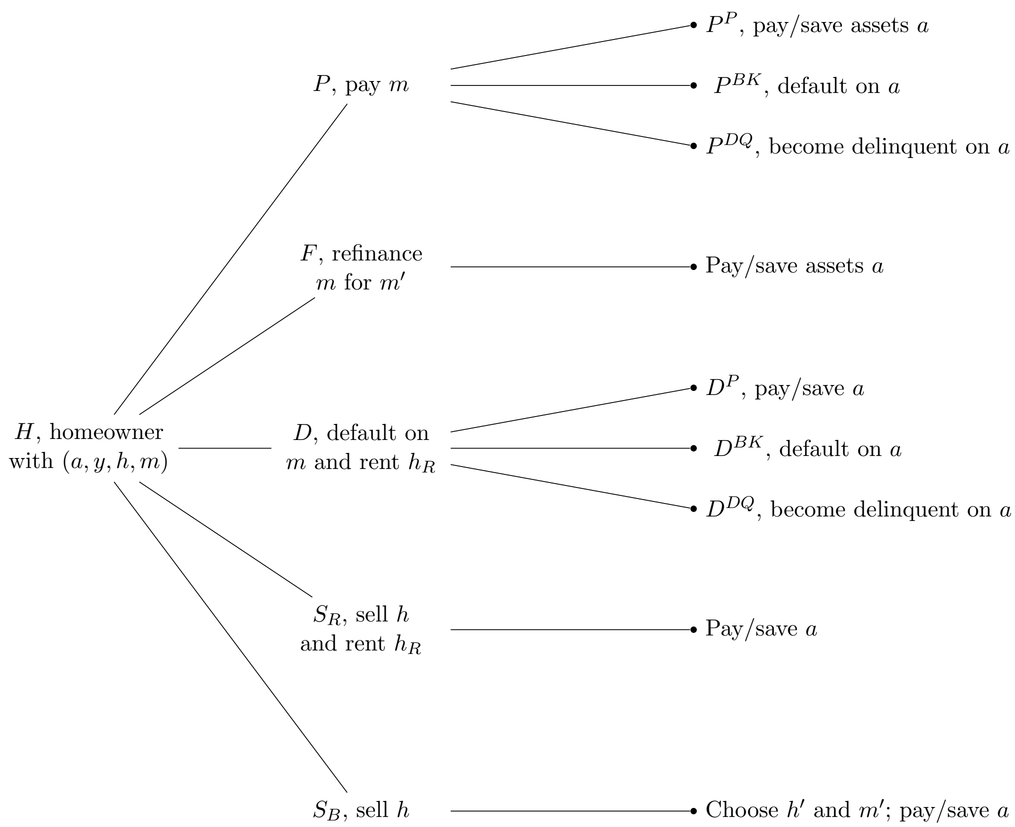


Figure 8 shows that a nonhomeowner N with assets a and income y can choose to either rent R or become a homebuyer B. If the agent chooses to rent, then she must decide whether to pay/save R^P her financial assets a, formally default on them R^{BK}, or cease repayment and therefore become delinquent R^{DQ}. Alternatively, if the agent chooses to become a homebuyer, then she must choose the size of the house to by h' and the mortgage to finance it m'. We assume that in the period of purchasing a home, agents are not able to repudiate financial debt a in any form.

Figure 9: Decision tree of a homeowner



Next, Figure 9 shows the choices available to an existing homeowner H with assets a, income y, living in a house of size h, and paying a mortgage m. Homeowners have five options. First, they can choose to pay P their mortgage m. Then, they must decide whether to pay/save P^P their financial assets a, formally default on them P^{BK}, or become delinquent P^{DQ}. Second, a homeowner can refinance F their existing mortgage m to obtain a new one

m'. Much like a homebuyer, we assume that in the period of refinancing a mortgage, agents are not able to repudiate financial debt a in any form. Third, homeowners can choose to default D on their mortgage. As a result of this mortgage default, these agents immediately become renters and therefore can also choose to repay D^P or repudiate their financial debt via delinquency D^{DQ} or bankruptcy D^{BK}. Fourth, homeowners can choose to sell their house and become renters S^R. We assume that in the period of selling a home, agents are not able to repudiate financial debt a in any form. Lastly, homeowners can choose to sell their house h and buy a new house of size h' with a new mortgage m'. Effectively, this implies the same optimization problem as that facing a homebuyer, detailed above, and so agents are not able to repudiate financial debt a.

In the next subsections, we sketch each decision problem and provide some additional details. A formal description of the recursive problems is presented in Appendix C.

3.1.1 Nonhomeowners

If the agent does not own a house, she must decide whether to rent a home, R, or buy one, B. Agents who rent can meet their existing financial obligations (or save), become delinquent on current financial debts, or formally default (bankruptcy). Meanwhile, agents who purchase a house must choose the size of the house and a corresponding mortgage and pay existing financial debts. We describe these problems below.

Renter and no financial asset default. A renter of discount factor type j, with income y, who decides not to default on financial assets can only choose next period's financial assets a'. Hence, the agent's budget constraint reads:

$$c + q^a_{j,n}(h_R, 0, a', y)a' = y + a.$$

Here y denotes income and q^a is the price (i.e., discount) applied to financial assets. As noted above, the fact that agents can repudiate debt means that its price will reflect default incentives, which in turn depend on the agent's state-vector, and hence on housing, income, and their discount factor type.

Renter and bankruptcy. A renter of type j with income y, who decides to formally default on financial assets a faces the following trivial budget constraint: $c = y - (\text{filing fee})$, where $filing\ fee$ is the bankruptcy filing fee.

Renter and delinquency. An agent who is a renter and decides to skip payments (i.e., become delinquent) on financial assets a faces the following constraints:

$$
\begin{aligned}
c &= y, \\
\\
a' &= 0, \quad \text{with prob. } \gamma, \\
a' &= (1 + r^R)a, \quad \text{with prob. } 1 - \gamma.
\end{aligned}
$$

Here, γ is the probability of discharging delinquent debt, and r^R is the roll-over interest rate on delinquent debt.

Homebuyer. An agent who is buying a house and income y and assets a must choose next period's financial assets a', the size of their house h', and the amount to borrow for the house m'. For a given tuple of income, assets, savings, house size, and mortgage size, the agent faces the following constraints:

$$
\begin{aligned}
c + q^a_{j,n}(h', m', a', y)a' &= y + a + q^m_{j,n}(h', m', a', y)m' - I_{m'>0}\xi_M - (1 + \xi_B)ph', \\
q^m_{j,n}(h', m', a', y)m' &\leq \lambda ph'.
\end{aligned}
$$

Here, p is the price of a house, and q^m is the price of a mortgage. The mortgage price depends on the house size, mortgage amount, income, and the agent's discount factor type j. The second equation is a loan-to-value (LTV) constraint implying that the LTV ratio cannot exceed an amount λ.

3.1.2 Homeowner

A homeowner's problem is more complex. On the financial asset dimension, homeowners must decide to default or repay their financial assets. On the housing dimension, homeowners can : (i) pay their current mortgage, (ii) refinance their mortgage, (iii) default on their mortgage, or (iv) sell their house and buy another one, or (v) become a renter. We describe these problems next.

Mortgage payer and no financial asset default. Agents who decide to pay their mortgage and their financial assets face the following budget constraint:

$$c + q^a_{j,n}(h, m(1-\delta), a', y)a' = y + a - m. \tag{1}$$

Notice that the bond prices these agents face depend on the size of their house h, tomorrow's mortgage size $m(1-\delta)$, the financial assets borrowed or saved a', income, and the agent's discount factor type j. The parameter δ captures the rate at which mortgage payments decay.

Mortgage payer and bankruptcy. Agents who decide to pay their mortgage but formally default on their financial assets have the following budget constraint $c = y - (\text{filing fee}) - m$, where $filing\ fee$ is the bankruptcy filing fee and m is the current mortgage payment.

Mortgage payer and delinquency. Households who decide to pay their mortgage but informally default on their financial assets face the following constraints:

$$\begin{aligned} c &= y - m, \\ \\ a' &= 0, \ \text{with prob.} \ \gamma, \\ a' &= (1 + r^R)a, \ \text{with prob.} \ 1 - \gamma. \end{aligned}$$

Mortgage refinancer. An agent who chooses to refinance cannot default on financial assets a, must prepay their current mortgage, choose next period's financial assets a', and choose the amount to borrow b' with their new mortgage. This problem can be thought of as a special case of a homebuyer who is "rebuying" their current home of size h but who has cash-on-hand equal to income y, plus financial assets a, minus fees from prepaying their current mortgage m. Thus, the constraints for this problem are:

$$
\begin{aligned}
c + q^a_{j,n}(h', m', a', y)a' &= y + a - q^*_n m + q^m_{j,n}(h', m', a', y)m' - I_{m'>0}\xi_M, \\
q^m_{j,n}(h', m', a', y)m' &\leq \lambda p h'.
\end{aligned}
$$

Here, $q^*_n m$ is the value of prepaying a mortgage of size m with n remaining periods worth of payments. Following Hatchondo, Martinez, and Sánchez [2015] the pricing function q^* is:

$$
q^*_n = \frac{1 - \left(\frac{1-\delta}{1+r}\right)^{n+1}}{1 - \frac{1-\delta}{1+r}}, \text{for} \quad n \geq 1,
$$

where δ is the rate at which mortgage payments decay.

Mortgage defaulter and no financial asset default. An agent who defaults on her mortgage and chooses not to default on her financial assets a immediately becomes a renter and must choose next period's financial assets a'. Thus, the budget constraint she faces is identical to that of a renter who pays her financial assets: $c + q^a_{j,n}(h_R, 0, a', y)a' = y + a$.

Mortgage defaulter and bankruptcy. Using the same reasoning as above, we can write the problem as a mortgage defaulter who chooses bankruptcy (on financial assets) as the problem of renter who files for bankruptcy. Thus, the budget constraint is simply:$c = y - filing\ fee$.

Mortgage defaulter and delinquency. Lastly, we can write the problem as a mortgage defaulter who chooses delinquency (on financial assets) as the problem of renter who is also delinquent on existing debt:

$$
\begin{aligned}
c &= y, \\
\\
a' &= 0, \text{ with prob. } \gamma, \\
a' &= (1 + r^R)a, \text{ with prob. } 1 - \gamma.
\end{aligned}
$$

Seller to renter. Recall, a home seller who decides to rent cannot default on financial assets. Hence, this problem is simply that of a renter with financial assets equal to a plus the gains from selling their current house. Thus, the agent's budget constraint reads:

$$c + q^a_{j,n}(h_R, 0, a', y)a' = y + a + ph(1 - \xi_S) - q^*_n m. \tag{2}$$

Here, the term $1 - \xi_S$ is a transaction cost from selling a house with value ph, and $q^*_n m$ is the value of prepaying a mortgage of size m with n periods left.

Seller to other house. Finally, a seller who decides to buy another house must also pay her financial obligations. Therefore, this agent's problem is just a special case of a homebuyer with cash on hand equal income plus current financial assets plus gains from selling the current house. As a result, we can write the constraints for this problem as:

$$\begin{aligned} c + q^a_{j,n}(h', m', a', y)a' &= y + a + ph(1 - \xi_S) - q^*_n m + q^m_{j,n}(h', m', a', y)m' \\ &- I_{m'>0}\xi_M - (1 + \xi_B)ph', \end{aligned}$$

$$q^m_{j,n}(h', m', a', y)m' \leq \lambda ph'.$$

3.1.3 Mortgage prices

When an agent of type j, with income y and financial savings a', asks for a mortgage that promises to pay m' next period, the amount she borrows is given by $m' q^m_{j,n}(h', m', a', y)$, where:

$$q^m_n(h', m', a', y) = \frac{q^m_{pay,j,n} + q^m_{prepay,j,n} + q^m_{default,j,n}}{1 + r}. \tag{3}$$

This equation reveals that the price of a mortgage depends on the likelihood that tomorrow this mortgage will be repaid (first term), prepaid (second term), or defaulted on. Recall, mortgage payment can occur alongside financial debt payment, default, or delinquency. Meanwhile, mortgage prepayment occurs whenever the agent refinances, sells her current house and rents, or sells her current house and buys another house. In all of these prepayment scenarios, financial debts cannot be repudiated. Lastly, mortgage default can occur alongside financial debt payment, default, or delinquency. Hence, under this formulation, mortgage prices internalize how financial asset positions today and tomorrow affect the probability of mortgage default.

3.1.4 Bond prices

When an agent of type j, income y, house size h', and mortgage size m' issues debt and promises to pay a' next period, the amount it borrows is given by $a'q^a_{j,n}(h', m', a', y)$, where:

$$q^a_{j,n}(h', b', a', y) \quad = \quad \frac{q^a_{pay,j,n} + q^a_{DQ,j,n}}{1+r}. \tag{4}$$

First, consider the price of payment tomorrow, $q^a_{pay,j}$. Conditional on being a nonhomeowner, this occurs in two scenarios: renter, no financial asset default, and homebuyer. Conditional on being a homeowner, payment occurs in five scenarios: mortgage payer, no financial asset default; mortgage refinancer; mortgage defaulter, no financial asset default; seller to renter; and seller to buyer. Regardless of home status, in all of these cases creditors get paid the same amount per unit of debt issued by the household.

Next, consider the price given delinquency tomorrow, $q^a_{DQ,j}$. Conditional on being a nonhomeowner, this occurs only when renters choose delinquency. Meanwhile, conditional on being a homeowner, this occurs in two cases: mortgage payer, delinquency; and mortgage defaulter, delinquency. In all of these cases debt gets rolled-over at a rate $(1+r^R)$ with probability $(1-\gamma)$. Importantly, though, tomorrow's price of this rolled-over debt will depend on housing status tomorrow. Hence, this bond pricing formula reveals that bond prices interact with housing status as the latter affects the likelihood of financial debt payment, default, and delinquency in the future.

3.2 Parameterization

Our approach to model parameterization is standard. We first directly set values for a subset of the most standard parameters. Second, given these first-stage values, we estimate the remaining parameters so that the model-simulated data match some key empirical features.

3.2.1 Assigning first-stage parameters

Table 2 collects the parameters set externally. A period in the model refers to a year; households enter the model at age 25, retire at age 65, and die no later than age 82. We set the risk-free interest rate at 3%. In addition, we externally calibrate the parameters governing the income process, bankruptcy filing costs, retirement, and mortality. We also externally set the initial distribution of wealth-to-earnings to match the distribution of wealth-to-earnings of 25-year-olds in the Survey of Consumer Finances between 1998 and 2016.

The utility u derived from consumption c and from living in a house of size h displays a constant elasticity of substitution between the two goods:

$$u(c,h) = \frac{((1-\theta)c^{1-1/\alpha} + \theta h^{1-1/\alpha})^{(1-\gamma)/(1-1/\alpha)}}{1-\gamma}$$

where: γ denotes the risk aversion parameter, α governs the degree of intra-temporal substitutability between housing and nondurable consumption goods, and θ determines the expenditure share for housing. Following Hatchondo, Martinez, and Sánchez [2015], we set γ to 2, α to 0.5, and θ to 0.11.

As previously mentioned, we follow Athreya, Mustre-del Río, and Sánchez [2019] and assume agents can either be patient β_H or impatient $\beta_L \leq \beta_H$. For simplicity, and following Athreya, Mustre-del Río, and Sánchez [2019], we set $\beta_H = 1.00$, which leaves β_L and the share of impatient types s_L as parameters to be determined.

The penalty rate for delinquent debt is set at 20% annually, following Livshits, MacGee, and Tertilt [2007]. Bankruptcy filing costs are at 2.8% of average income, or roughly \$1,000, again following Livshits, MacGee, and Tertilt [2007].

Turning to the income-process parameters, we consider restricted-income-profile (RIP) type income processes following Kaplan and Violante [2010]. During working ages, income has a life-cycle component, a persistent component, and an i.i.d component:

$$log(y^i_{n,t}) = l(n) + z^i_{n,t} + \epsilon^i_{n,t}$$

where: $l(n)$ denotes the life-cycle component, $\epsilon^i_{n,t}$ is a transitory component, and $z^i_{n,t}$ is a persistent component that follows:

$$z^i_{n,t} = z^i_{n,t-1} + e^i_{n,t}.$$

We assume $\epsilon^i_{n,t}$ and $e^i_{n,t}$ are normally distributed with variances σ^2_ϵ and σ^2_e, respectively.

While in retirement, the household receives a fraction of the last realization of the persistent component of its working-age income using the replacement ratio formula: $\max\{A_0 + A_1 exp(z^i_{W1}), A_2\}$. In order to be consistent with U.S. replacement ratios, we calibrate A_0, A_1, and A_2 such that the replacement ratio declines with income, from 69% to 14%, with an average replacement rate of 47%. The age-specific survival probabilities follow Kaplan and Violante [2010].

Table 2: Externally set parameters

Parameter	Value	Definition	Basis
l	–	Life-cycle component of income	Kaplan and Violante [2010]
W	65	Retirement age	U.S. Social Security
ρ_n	–	Mortality age profile	Kaplan and Violante [2010]
a_0	–	Initial financial asset distribution	Survey of Consumer Finances 1998-2016
σ^2_ϵ	0.063	Variance of ϵ	Kaplan and Violante [2010]
σ^2_e	0.0166	Variance of e	Kaplan and Violante [2010]
r	0.03	Risk-free rate	Standard
γ	2	Risk aversion	Standard
α	0.5	Elasticity of substitution	Standard
θ	0.11	Consumption weight of housing	Hatchondo, Martinez, and Sánchez [2015]
β_H	1.00	Discount factor of patient types	Athreya, Mustre-del Río, and Sánchez [2019]
ξ_B	0.03	Cost of buying a house, households	Gruber and Martin [2003]
ξ_S	0.03	Cost of buying a house, households	Gruber and Martin [2003]
$\bar{\xi}_S$	0.22	Cost of selling a house, banks	Pennington-Cross [2006]
ξ_M	0.15	Cost of signing a mortgage	U.S. Federal Reserve
δ	0.02	Payments decay	Average inflation
A_0	0.7156	Replacement ratio	U.S. Social Security
A_1	0.04	Replacement ratio	U.S. Social Security
A_2	0.14	Replacement ratio	U.S. Social Security
λ	1	LTV limit	Positive down payment
f	0.028	Cost of filing for bankruptcy/ average income	Livshits, MacGee, and Tertilt [2007]
r_R	0.2	Roll-over rate on delinquent debt	Livshits, MacGee, and Tertilt [2007]

3.2.2 Estimating the remaining parameters

The remaining parameters to be determined are: β_L the discount factor of impatient types, s_L the share of impatient types in the population, η the probability of delinquent debt being fully discharged, h_R the size of rental houses, p the mean house price, and λ the loan-to-value ratio limit. We estimate these parameters so that model-simulated data replicate some key features of the data pertaining to homeownership, financial wealth, and FD.

Table 3 presents the model's performance in matching the empirical targets. As can be seen from this table, the model does a good job of matching salient features of the financial asset distribution, homeownership, home values relative to income, and initial loan-to-value ratios, which are critical to get an empirically plausible housing leverage distribution. Additionally, the model also matches average mortgage default rates and FD via delinquency or bankruptcy.

Table 3: Calibration targets

Calibration target	Source	Data	Model
Mean (savings/inc)	SCF 2007	1.98	1.93
Homeownership rate (in %)	SCF 2007	68.00	68.76
Mortgage default rate (in %)	JKM [2013]	0.50	0.51
Bankruptcy rate (in %)	LMT [2007]	0.84	0.85
Mean DQ rate (in %)	Equifax	14.40	13.85
Mean (home value / income), owners	SCF 2007	3.81	3.89
Mean LTV, owners	MIRS 2006	0.76	0.70

Table 4 presents the model's implied parameter values. Similar to Athreya, Mustre-del Río, and Sánchez [2019], the model requires a significant amount of discount factor heterogeneity to generate sufficient financial distress while also generating an empirically plausible financial wealth distribution. Additionally, the model requires a reasonably high discharge probability of delinquent debt to make the informal default margin attractive relative to formal bankruptcy. Lastly, the model does not require a very tight loan-to-value constraint in order to generate empirically plausible loan-to-value ratios.

Table 4: Model parameter estimates

Parameter	Value
Low discount factor β_L	0.51
	(0.12)
Discharge prob. γ	0.59
	(0.21)
Rental house size h_R	1.17
	(0.14)
House prices p_H	6.25
	(0.52)
share of pop. of type L	0.32
	(0.82)
LTV λ	0.90
	(0.42)

Notes: Asymptotic standard errors appear in parentheses.

4 Quantitative Exercises

We can now use the model to better understand how the relationship between financial distress and housing wealth affected the dynamics of consumption during the Great Recession. This requires, first of all, that we generate within the model a stylized Great Recession. We then proceed to inspect the micro-level mechanisms at work in our model and confirm they are at play in the data.

4.1 Engineering a recession

A central aspect of the Great Recession was that it was characterized by a large drop in home prices followed by a decline in income. Taking both as exogenous and unanticipated, we replicate these events in our model. We find that each of these two shocks amplify the other and that the magnitude of amplification critically depends on the covariance between house price shocks and financial distress. Thus, our model, even though in no direct way engineered to generate such features, produces outcomes much like our empirical findings.

Specifically, we first subject the stationary distribution of the economy to an unanticipated (but permanent) house price decline. Importantly, to mimic the empirics from the previous sections, we assume that house price shocks are positively correlated with financial distress, but on average lead to a 10% decline in house prices.[6] In the period immediately following the house price shock, we further subject the economy to an unanticipated (again, permanent) 3% income decline, which is uniformly experienced across all individuals. We then compute the drop in aggregate consumption. The top row of Table 5 summarizes the results.

The first row of Table 5 suggests that the Great Recession, as captured in these two shocks, caused a significant decline in aggregate consumption. We see in our experiment that an average house price decline of 10%, followed by a 3% decline in income, results in a 3.4% decline in aggregate consumption (Row 1). Importantly, however, this headline number depends on correlation between house price shocks and FD, the key empirical finding from the previous section. Row (2) of this table shows that if the 10% house price decline

[6] In these exercises the house price decline for individuals in FD is roughly three times larger than the house price decline for individuals not in FD, which roughly matches the housing shocks faced by zip codes in the top quintile of FD versus first and second quintiles.

Table 5: Engineering a recession

Scenario	Av. % change in C	Av. % change in FD
(1) Corr. house shock then income shock	-3.4	4.2
(2) Uniform house shock then income shock	-2.9	3.7
(3) Income shock alone	-1.6	0.0
(4) Corr. house shock alone	-1.6	4.1
(5) Uniform house shock alone	-1.1	3.5

Notes: Here the average percentage change in consumption (FD) is the percentage change relative to the steady-state level of consumption (FD) averaged between the year of the initial shock and the next two years after the shock.

is uniformly experienced by all individuals regardless of FD, the resulting decline in aggregate consumption is less at 2.9%. Thus, the positive covariance between house price shocks and FD leads to an additional 0.5 percentage point drop in aggregate consumption when these shocks precede an income shock. Alternatively, we can focus on the role of house shocks alone (and the covariance structure) by comparing Rows (4) and (5). Here too we find that housing shocks correlated with FD lead to an additional 0.5 percentage point drop in aggregate consumption relative to a case when housing shocks are uncorrelated with FD. Thus, what we label as the covariance channel of FD amplifies the drop in consumption due to house prices by 45% (i.e., 0.5/1.1).

While the previous calculations highlight the importance of the covariance between house price shocks with FD, they do not address how house price shocks and income shocks interact and amplify each other. To quantify the amplification/timing aspect, we can compare the individual effects of housing shocks or income shocks alone with their joint effect. For example, adding Rows (3) and (4) combines the independent effects of income and correlated housing shocks. They result in a 3.2 percentage point drop in aggregate consumption, which is 0.2 percentage point less than what is reported in Row (1), when the correlated housing shock precedes the income shock. For uncorrelated housing shocks we can perform a similar calculation by adding Rows (3) and (5) and comparing the result to Row (2). Adding the two independent effects leads to a 2.7 percent decrease in aggregate consumption, which again is 0.2 percentage point less relative to the case when the uniform housing shock precedes the income shock. Thus, what we label as the amplification or timing channel of FD accounts for an amplification of 6 to 7% (i.e., 0.2/3.2 or 0.2/2.7) in the drop in aggregate consumption, depending on whether housing shocks are correlated or not.

Finally, the second column of Table 5 shows how the aggregate level of FD responds to each of the shocks. The main conclusion from this column is that FD mostly reacts to changes in house prices but not changes in income. Indeed, Row (3) shows that income shocks alone generate essentially no change in FD, whereas Rows (4) and (5) suggest FD reacts strongly to house price shocks, whether they are correlated with FD or not. To put Rows (4) and (5) into perspective, recall the steady-state level of FD is approximately 14%. So, these percentage point differences are about 25 to 29% of the steady-state level of FD.

Overall, the results from this subsection highlight three things. First, the observed covariance between house price shocks and FD is quantitatively important for generating drops in consumption compared to a scenario where house price shocks are uniformly distributed across individuals regardless of distress. Our calculations suggest correlated house price shocks increase the drop in consumption relative to the uniform case by 45% (equivalent to 0.5 percentage points). Second, our model implies a nontrivial role for the interaction between house price shocks and income shocks. Indeed, a naive addition of the independent effects of these two shocks misses between 6-7% of the total drop in consumption (equivalent to 0.2 percentage points) when the two shocks are combined. Third, the aggregate level of FD reacts strongly to house price shocks but not to income shocks. Thus, this suggests increases in FD are associated with large consumption drops. In the next section, we discuss the direct link between FD and changes in consumption.

4.2 Inspecting the mechanism: the importance of FD

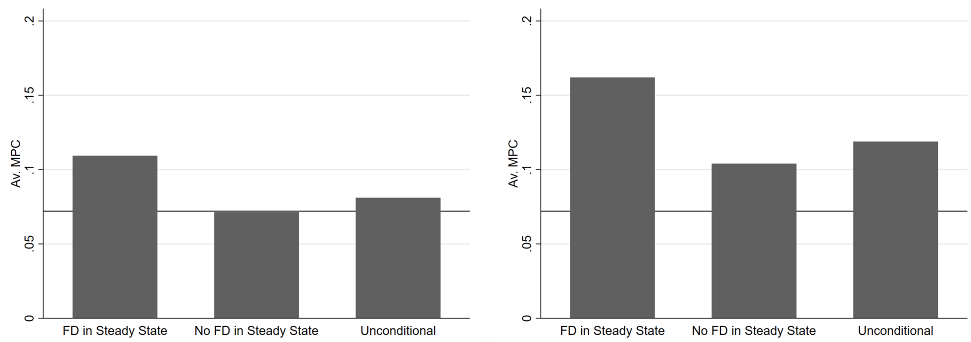
A key conclusion from the results in the previous subsection is that the covariance between FD and house price shocks significantly matters for the response of aggregate consumption. In this section, we show that this occurs for two reasons. First, as previously described, the level of FD is very responsive to house price shocks. Second, and more importantly, individuals in FD in general have more elastic consumption responses to shocks. Thus, with these two results it should come as little surprise that when house price shocks land more heavily on people in FD, the response of consumption is greater.

To see that individuals in FD tend to have more elastic consumption responses to shocks, consider Figure 10, which plots the marginal propensities to consume (MPC) out of housing shocks for the two types of shocks we consider. The left panel of this figure plots the MPCs when shocks are correlated with FD, whereas the right panel plots MPCs when housing shocks are uncorrelated with FD. Focusing on the left panel, the first two bars show that individuals who in steady state are in FD have an MPC out of housing shocks of roughly 11 cents (in model units of nondurable consumption) for every dollar of housing wealth lost. In contrast, individuals who in steady state are not in FD have an MPC out of housing shocks of roughly 7 cents for every dollar of housing wealth lost. Overall, when housing shocks are correlated with FD, our model implies an MPC out of housing wealth of nearly 8 cents, which is very close to the IV-estimate of the MPC out of housing wealth reported by Mian et al. [2013] of 7.2 cents (depicted by the solid horizontal line). The right panel of Figure 10 shows that qualitatively the same patterns emerge when housing shocks are uncorrelated, but quantitatively the numbers differ. Indeed, even when housing shocks are independent of FD, individuals in FD tend to have higher MPCs than those not in FD. However, the magnitudes are larger. Individuals in FD have an MPC of roughly 16 cents, about 5 cents higher than in the case with correlated housing shocks. Meanwhile, individuals not in FD have an average MPC of roughly 10 cents, which is about 3 cents larger than in the case with correlated housing shocks. That the MPCs rise with uniform housing shocks, particularly for those in FD, reveals that in our model MPCs are a nonlinear function of the size of the shock: higher for for smaller shocks, and lower for bigger shocks.

Table 6 shows that the decline in consumption for people in FD is particularly salient for homeowners, using the case of a uniform 10% house price decline as an example. As can be seen from the first row of this table, the average percent change for homeowners in FD ranges from -4.5 to -5.5 percent depending on the severity of FD. This contrasts sharply with the much smaller average increases in consumption for homeowners not in FD and the muted response of nonhomeowners in general.[7]

[7]This is consistent with Aladangady [2017], who finds a negligible response of renters to house price shocks.

Figure 10: MPC out of Housing Wealth in Model-Simulated Data



(a) Shock Covarying with β (b) Uniform Shock

Note: The dark horizontal line corresponds to the MPC out of a dollar change in housing wealth found by Mian et al. [2013] in their instrumental variable estimation. As before, we report the "Average MPC" between the period of the shock and the period after relative to a counterfactual in which the steady state had continued. "FD in Steady State" refers to being in FD in either the first or second period of that counterfactual.

Table 6: Consumption Responses to a Housing Shock by Financial Distress and Homeownership.

FD Group	Av. % chg. in C	share of pop	share β_L	FD in shock
Homeowners in Year of Shock				
High FD	-5.5	5.7	93.9	44.4
Low FD	-4.5	18.7	74.9	52.6
No FD	1.4	53.8	1.78	2.0
Nonhomeowners in Year of Shock				
High FD	0.4	10.5	99.6	53.5
Low FD	2.5	1.8	61.2	30.9
No FD	-1.7	9.5	0.1	0.1

Note: The "No FD" group includes individuals who have not been in FD for the last six time periods. Among those with some FD over the last six time periods, the 50th percentile of time spent in FD was found, and agents were divided into "high" and "low" FD based upon that threshold. Note that because this grouping is done based on the last six time periods, agents who have been in the model for fewer than six periods are omitted.

Table 7 goes further into detail to understand the interaction between homeowners and FD status in shaping their consumption response to house price shocks. Specifically, this table presents the average consumption responses conditional on the optimal response *absent the house price shock* (i.e., in steady-state) and conditional on the optimal response given the house price shock. For example, among homeowners in the year of the shock, the first row denoted by "Pay/Pay" displays the average consumption response by individuals who in steady state pay their mortgage and still pay their mortgage after the house price shock hits. Because Table 7 is meant to illustrate the mechanisms at hand and because there are many possible combinations of steady-state/shock decisions, we choose to present only the most quantitatively salient ones.

The key message from the top panel of this table is that among homeowners the refinance channel is critical for generating large declines in consumption for financially distressed homeowners. Note that individuals who in steady-state refinance but given the shock pay their mortgage (Refi/Pay) see their consumption decline by on average 5.7%. Recall, these are responses to a 10% uniform house price shock, suggesting the pass-through of this shock into nondurable consumption is over 50%. In the steady state of the model, these individuals are using the refinance channel to extract equity from their houses to finance nondurable consumption. Importantly, because a large share of these individuals are effectively impatient (81% of them have low discount factors) and have a history of being in FD, they face high borrowing costs in the unsecured credit market; hence, they turn first to refinancing. Once house prices decline, these individuals lose home equity and the refinance option becomes unavailable to them. As a consequence, many of these individuals continue (or enter) in FD, face even higher borrowing costs (because now their net worth position is even worse), and cut their consumption dramatically. Also note that individuals who refinance regardless (Refi/Refi) also cut their consumption in response to the house price shock but by much less since fewer of these individuals are in FD to begin with.

The bottom panel of Table 7 helps to clarify the mechanisms behind the more modest responses to house price shocks of nonhomeowners. The bulk of nonhomeowners not only do not own a house, but also do not plan to buy one in steady-state or when house prices decline. We denote this group as (Don't Buy/Don't Buy). Naturally, perhaps, their consumption moves very little when the shock hits: the shock is essentially irrelevant. Nonhomeowners who eventually are likely purchase a house regardless of the house price shock, whom we denote as (Buy/Buy), increase their nondurable consumption quite substantially because now houses are cheaper. Lastly, and in contrast to the previous group, nonhomeowners who purchase a house *because* of the house

Table 7: Consumption Responses to a House Price Shock by Detailed Homeownership.

Steady State / Shock	Av. % chg. in C	share of pop	share β_L
Homeowners in Year of Shock			
Pay/Pay	-0.9	45.4	14.7
Refi/Pay	-5.7	11.5	80.8
Refi/Refi	-1.8	6.1	10.2
Sell then Buy/Sell then Buy	5.1	1.2	21.1
Nonhomeowners in Year of Shock			
Buy/Buy	6.0	2.5	38.9
Don't Buy/Buy	-7.7	1.2	33.8
Don't Buy/Don't Buy	-1.1	27.3	47.5

Note: The first column categorizes individuals by their decisions under the steady state and their new decisions under the shock. "Pay" and "Refinance" refer to paying or refinancing the mortgage. "Sell" and "Buy" here refer to selling or buying homes. Some small categories have been omitted for brevity. Av. % Change gives the percentage change from steady state between the year of the shock and the year after the shock.

price shock (Don't Buy/Buy) decrease their nondurable consumption quite substantially because even though houses are cheaper, their financial asset position still requires them to cut back on nondurable consumption to finance housing.

To summarize, this subsection reveals three critical facts that help understand the aggregate consumption changes described in the previous section. First, in our model, individuals in FD tend to have larger consumption responses to changes in house prices. Second, this is disproportionately due to homeowners in FD. Third, the main reason why homeowners in FD react strongly is because the refinance channel dries up with house price declines: individuals who tend to smooth consumption by refinancing their mortgages are also systematically more likely to be in FD. When house prices fall, they lose home equity and therefore can no longer smooth consumption by refinancing. As a result, their consumption falls.

4.3 Are Financially Distressed Households Really More Responsive to Housing Shocks?

The results from the previous two subsections show that in our model at an aggregate level, higher FD is associated with larger consumption declines. At the individual level, agents cut their consumption more drastically not because of their FD status per se, but rather because of what this status summarizes. Using the case of homeowners as an example, those in FD are mostly impatient types with long histories of facing high borrowing costs in the unsecured credit market. As a result, their consumption is mainly financed through other means like mortgage refinancing. When housing and income shocks arrive, these means vanish and they respond by aggressively cutting consumption.

While we lack sufficiently detailed data at the individual level to corroborate this mechanism, we can still ask at a more aggregate level whether consumption in regions with higher FD actually responds more to housing price shocks? We argue that the answer is "yes." To this end, we estimate the marginal propensity to consume (MPC) out of housing shocks following the seminal work of Mian, Rao, and Sufi [2013]. In particular, we want to determine whether MPCs vary in a significant fashion by FD holding constant other regional features like income, wealth, etc.

Formally, we estimate regressions of the form:

$$\Delta C_t^i = \alpha + \beta_1 \Delta HV_t^i + \beta_2 FD_t^i + \beta_3 (\Delta HV_t^i \times FD_t^i) + \beta_4 X_t^i + \epsilon_t^i. \tag{5}$$

Here, ΔC_t^i represents the dollar change in consumption in geographic region i between t and $t+1$; ΔHV_t^i is the change in house value; FD_t^i is the level of financial distress in region i at time t; X_t^i is a vector of other regional covariates that can be both in levels and changes; and ϵ_t^i represents classical measurement error. The coefficients of central interest are: (i) β_2, the coefficient on financial distress, and (ii) β_3, the *interaction* between financial distress and housing shocks. To mitigate endogeneity problems, we follow Mian, Rao, and Sufi [2013] and instrument for changes in house value using housing supply elasticities as in Saiz [2010]. Additionally, we focus on new auto purchases as our measure of consumption at the county level. In terms of timing, all initial levels are measured in 2006, while all changes are measured between 2006 and 2009.

Table 8 reports the second-stage results of estimating equation (5). All columns reveal statistically significant coefficients at the 0.001 level for house price shocks (i.e., the change in home value between 2006 and 2009) and the interaction of these shocks with financial distress. Comparing across columns suggests that our estimated coefficients are robust to the definition of financial distress we use (e.g., DQ30, CL80, or a combination of the two). Importantly, because our regression includes interaction terms it is easiest to interpret these coefficients with some examples.

Table 8: Auto spending at the county level (IV)

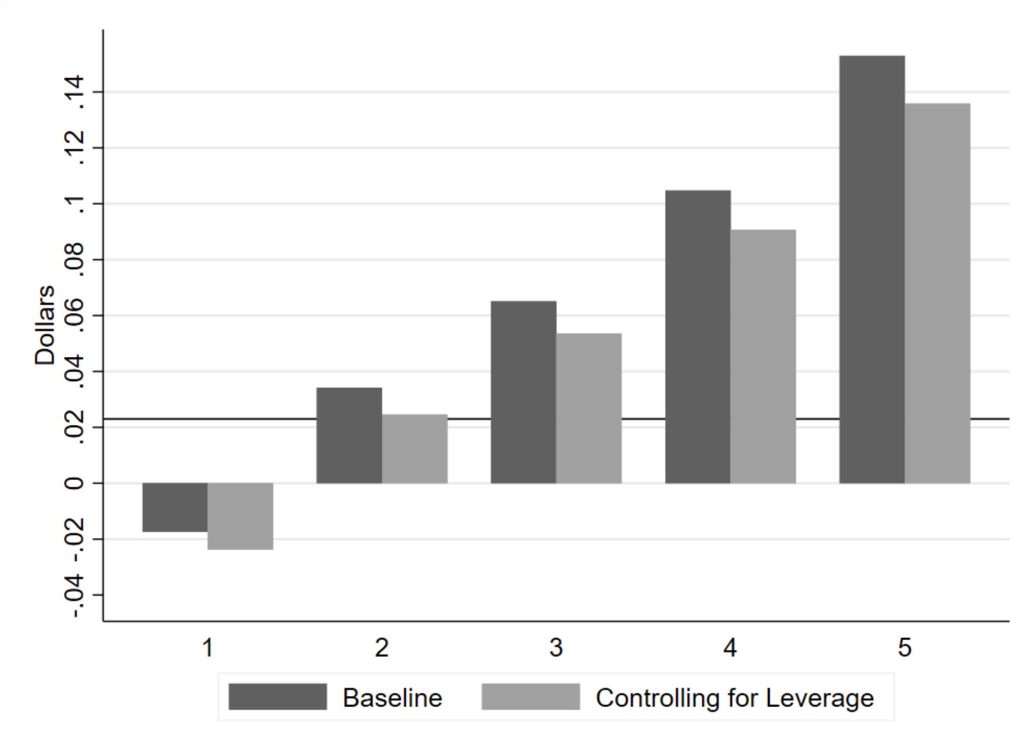
	Δ_{06-09} Auto Spending		
	(1)	(2)	(3)
Δ_{06-09} Home Value	-0.367***	-0.459***	-0.403***
	(0.09)	(0.10)	(0.10)
DQ30 (current year)	-60.302		
	(31.47)		
Δ_{06-09} Home Value $\times$ DQ30 (current year)	1.722***		
	(0.40)		
CL80 (current year)		-95.053***	
		(27.23)	
Δ_{06-09} Home Value $\times$ CL80 (current year)		1.611***	
		(0.34)	
CL80 and DQ30 (current year)			-87.530**
			(33.51)
Δ_{06-09} Home Value $\times$ CL80 and DQ30 (current year)			1.700***
			(0.43)
Observations	623	623	623

Notes: Controls include change in income and change in financial wealth and the interaction of these variables with the alternative variables of FD. We additionally control for the percent of households that owned homes in 2006 and include a constant. All regressions are weighted by the number of owner-occupied housing units in the county as of 2006. Standard errors appear in parentheses.

Sources: IRS SOI, CoreLogic HPI, IHS Markit, FRBNY Consumer Credit Panel/Equifax, Census Bureau.

Figure 12 shows how the coefficients in Column (2) of Table 8 translate into differing MPCs by level of financial distress. The dark set of bars represent the average MPC out of a dollar change in home values (between 2006 and 2009) for counties in a given quintile of financial distress as measured by our CL80 measure. The lighter set of bars represent the corresponding average MPCs under a specification where we also control for leverage. The key observation from this figure is that MPCs rise quite dramatically with financial distress, and this is true even after we account for differences in leverage across low and high FD regions. Using the dark bars as an example, while the top quintile of financial distress has an MPC out of a dollar change in housing value of 15.3 cents, the representative individual from the bottom quintile of FD has an MPC that is essentially zero (-1.7 cents).

Figure 12: Marginal Propensity to Consume out of a Dollar change in home prices by Quintile of CL80 in 2006.



Notes: Group means are weighted by the number of owner-occupied housing units per county as of 2006. The horizontal line corresponds to the mean MPC out of autos estimated by MRS13.

Overall, these empirical results support the quantitative mechanisms highlighted in the previous subsections. Moreover, they are also consistent with the recent literature on consumption responses to house price shocks as exemplified by Mian et al. [2013] and Aladangady [2017], among others. However, these results are not intended to establish a causal relationship between financial distress and observed consumption declines. Indeed, our model suggests financial distress is a useful summary statistic capturing a history of high borrowing costs induced, in part, by impatience. Rather, these results corroborate our model's quantitative implications.

5 Conclusions

In this paper, we uncover a previously unknown channel–financial distress–that we argue mattered significantly for observed consumption dynamics during the Great Recession. Our contribution is to provide both empirics and quantitative theory. Empirically, we show that prior to the Great Recession, consumers were very differentially positioned with respect to their status in the credit market. Specifically, zip-code-level data show large variation in the proportion of individuals either delinquent on debts or having nearly exhausted stated credit limits. Additionally, we demonstrate that regions with a higher incidence of FD prior to the Great Recession systematically suffered larger house price declines at the onset of the recession. We then develop a rich dynamic model of consumption and credit use that allows for variation in homeownership, debt repayment behavior, and creditor response to consumer default risk. We use the model to show that FD amplified the drop in aggregate consumption by up to 45 percent. A key reason for this finding is that in the model individuals in FD tend to have higher marginal propensities to consume (MPC) out of housing shocks. Thus, the aftermath of the Great Recession should come as little surprise. Not only did the share of people in FD increase, people in FD were also disproportionately buffeted by the worst housing shocks.

In identifying FD, or proximity to it, as a key amplifier of shocks, our findings reinforce the message first discovered and conveyed by Mian et al. [2013] and Mian and Sufi [2010] that macroeconomic outcomes run through household balance sheets and credit health. The shock of relevance here, that of a sharp unanticipated drop in house prices, makes the lessons of our model somewhat general. As Mian and Sufi [2010] have argued, housing busts lie behind the most severe downturns that most economies experience. Our work emphasizes that measures which capture individuals' difficulties with creditors, which we coin financial distress, are valuable in gauging macroeconomic vulnerability and provide information in addition to that encoded in leverage or net worth. Our findings suggest that macroprudential policy may be well advised to track either or both of the measures of FD we have provided. Such measures, as we show, contain granular information relevant to forecasting not only the severity of damage to regional consumption, and in the short run, regional incomes arising from shocks to asset prices, but the size of the shocks themselves.

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A Empirical Results

A.1 Data

Summary statistics for our data are shown in Table 9.

Table 9: Descriptive Statistics

	Count	Mean	S.D.	p25	p50	p75
			County-level			
Housing Net Worth Shock, 2006-9	1083	-0.073	0.10	-0.109	-0.035	-0.008
Financial Net Worth Shock, 2006-9	1083	-0.10	0.01	-0.109	-0.102	-0.095
Change in home value (ths \$), 2006-9	1083	-60.73	84.96	-78.219	-24.070	-4.122
Net Worth per Household (ths \$), 2006	1083	522.96	377.04	295.81	427.23	622.69
Income Per Household, (ths \$), 2006	1083	73.68	26.15	55.993	69.126	82.413
No. of hhds per county (ths), 2006	1083	429.5	641.8	77.193	211.961	486.391
Housing Leverage Ratio, 2006	1083	0.487	0.123	0.399	0.469	0.570
Δ auto spending per hhd (ths \$), 2006-9	1083	-2.47	11.17	-8.564	0.519	4.850
Housing Supply Elasticity, Saiz	623	1.78	0.99	0.975	1.606	2.340
Fraction in CL80, 2006	1083	.237	.036	.213	.236	.264
Fraction in DQ30, 2006	1083	.149	.034	.126	.147	.171
			Zip-code level			
Housing Net Worth Shock, 2006-9	6901	-0.12	0.21	-0.17	-0.05	-0.01
Financial Net Worth Shock, 2006-9	6901	-0.10	0.02	-0.11	-0.10	-0.09
Change in home value (ths \$), 2006-9	6901	-67.65	94.41	-99.63	-29.01	-4.71
Net Worth per Household (ths \$), 2006	6901	556.45	847.86	203.05	339.09	593.87
Income Per Household (ths \$), 2006	6901	76.00	50.95	47.58	62.76	87.40
No. of hhds per Zip Code (ths), 2006	6901	13.03	5.78	8.91	12.35	16.33
Housing Leverage Ratio, 2006	6901	0.46	0.19	0.34	0.44	0.55
Fraction in CL80, 2006	6901	.234	.077	.180	.231	.284
Fraction in DQ30, 2006	6901	.144	.064	.097	.140	.185

Note: All statistics are weighted by the number of households in the first quarter of 2006 for each geography. p25, p50, and p75 respectively give the 25th, 50th, and 75th percentiles.
Sources: IRS SOI, CoreLogic HPI, FRBNY Consumer Credit Panel/Equifax, Census Bureau, Zillow, Federal Flow of Funds.

A.1.1 Building a geographically representative sample

Building a geographically representative sample over all the years considered in this study from Equifax presents a slight challenge: small random samples from FRBNY CCP/Equifax will give good estimates at the national level, and even for the largest zip codes, but poor estimates for the smallest zip codes. Using much larger random samples could fix this issue, but the resulting datasets become difficult to process. Instead, then, we divide the zip codes for which we have IRS SOI data into 10 groups by population size and over sample areas with lower population.

Specifically, we pull a 75% sample of individual Equifax records from the smallest zip codes by population and decrease that percentage linearly until pulling a 5% sample of Equifax records for the largest zip codes. In order to remain in our sample for a given quarter, individuals must be between 25 and 65 years old, inclusive.[8] Then, we correct for over sampling by reweighting using population data from the 2000 and 2010 Census.

For the maps in Figure 3, we use this same method but with a larger sample, pulling 100% of individual Equifax records for the smallest zip codes by population and decreasing that percentage linearly until pulling a 50% sample of the largest zip codes.

A.1.2 Household Net Wealth

The household wealth portion of our dataset was constructed at the zip code and county levels using a method almost identical to that of MRS13. Net wealth is defined as the sum of housing wealth H and financial wealth FW less debt D, where FW can be further broken down into stocks S and bonds B. H is calculated as the median home value multiplied by the number of owner-occupied housing units in each geography. We use Zillow data for home values and Census data on owner-occupied housing units.[9] This is done separately for zip codes and for counties. With a measure of total housing wealth in a geography thus defined, we calculate the housing leverage ratio as the total housing debt in a geography divided by the total housing wealth. Total housing debt is the mean housing debt, including both mortgages and home equity lines of credit[10] recorded in Equifax, in

[8] Age is calculated using an individual's recorded birth year, and so any records not including a birth year are also excluded.

[9] To fill in the missing years in Census data, we interpolate owner-occupied housing units linearly for each zip code and county from 2000 to 2010. MRS13 did not use Zillow data for home values and instead relied entirely on home price information from the 2000 Census tracked upward through time by the Core Logic price index. Using Zillow data affords us the advantage of much wider data coverage.

[10] This includes both the home equity installment balance and the home equity revolving balance.

each geography multiplied by the number of households in that geography, taken from the Census.

In the model calibration, we will at certain points use information from Equifax on whether a person has mortgage or HELOC debt as a proxy for whether they own a home. The advantage of this proxy is that because we observe it at the individual level in Equifax, we can directly calculate the percentage of people who are both under financial distress and have housing debt. Its accuracy for this purpose is discussed in Section 2.1.

To construct FW, we began by using IRS Summary of Income (SOI) data to calculate the fraction of national interest and dividends held by a given zip code. Then, each zip code was apportioned a share of the national stocks and bonds recorded in the Federal Flow of Funds[11] corresponding to that fraction. FW at the county level is simply calculated as the sum of FW in its component zip codes.[12] D is calculated in a similar fashion to FW. First, we calculate the fraction of the total debt balance in our sample of the Equifax dataset accounted for by a given zip code or county. Because our method of pulling Equifax data intentionally over sampled geographic areas with lower populations, we weight each geography's debt by the number of households it encompasses.[13] Next, we assign each geography a portion of the "Total Household and Nonprofit Liabilities" from the Federal Flow of Funds equal to that fraction.

In addition to the types of debt that MRS13 tracks, we also include a measure of credit card debt at the zip code and county levels. Here, we take the mean credit card debt by household in our Equifax sample and multiply that by the number of households in each geography.

With net wealth thus defined, we are in a place to calculate the change in net wealth over the Great Recession. MRS13 calculated this with geography index i as

$$\Delta NW^i_{06-09} = \Delta_{06-09}\log(p^S) * S^i_{06} + \Delta_{06-09}\log(p^B) * B^i_{06} + \Delta_{06-09}\log(p^{H,i}) * H^i_{06}$$

[11] Specifically, we consider stocks to be corporate equities, both directly and indirectly held. Then, bonds are given by Total Financial Assets for households and nonprofits less stocks.

[12] To avoid double counting FW, this requires that something be done about zip codes that span multiple counties. We elected to assign all of a zip code's FW into the county that most people in that zip code inhabit.

[13] Data on the number of households in each zip code and county come from the Census and was interpolated linearly from 2000 until 2010. More information on the Equifax sampling procedure is provided in appendix section A.1.1.

where p^S is given by the S&P500 index, p^B is given by the Vanguard Bond Index, and $p^{H,i}$ is the Core Logic house price index.[14] They then refer to

$$\frac{\Delta_{06-09}\log(p^{H,i}) * H^i_{06}}{NW^i_{06}}$$

as the housing net worth shock, and we will analogously refer to

$$\frac{\Delta_{06-09}\log(p^S) * S^i_{06} + \Delta_{06-09}\log(p^B) * B^i_{06}}{NW^i_{06}}$$

as the financial net worth shock.

A.1.3 Consumption

We use data from R.L. Polk by IHS Markit to find the quantity of new automobiles registered in each year by residents of each county. As noted by MRS13, these data are advantageous relative to other sources of consumption data because they record where the car buyer lives rather than the point of sale, but disadvantageous in that they do not include the price of each vehicle purchased. To resolve this issue, we follow after MRS13 in allocating an annual share of the national Census Retail Trade amounts for "Auto, Other Motor Vehicle" to each county equal to the share of new autos that county purchased in the Polk data. By construction, then, the aggregate auto expenditures in our sample will accurately reflect the national difference from 2006 to 2009, but measurement error will be present at the county level to the extent that auto prices did not evolve in the same way across counties from 2006 to 2009. If the price of pickup trucks dropped more than other types of cars, for example, and a particular rural county purchases mainly pickup trucks, then our data will underestimate the decrease in car consumption for that county just as MRS13 did.

A.1.4 Financial Distress

Several different metrics of FD are used to test the robustness of our conclusions. As defined in Section 2.1, DQ30 gave the percentage of primary

[14] The Core Logic house price index is available at both the county and zip code levels, and so we calculate the home price changes at each level directly rather than deal with the possible errors that could arise from aggregating zip-code-level shocks to the county level.

borrowers in the Equifax dataset who are at least 30 days delinquent on a credit card payment during some quarter of the year. CL80 was similarly defined for primary borrowers as the percentage of people who have reached at least 80% of their credit limit during some quarter of the year.

With these two definitions in place, the remaining metrics combine the two in different ways. "DQ30 and CL80 (current year)" calculates for each individual the portion of quarters in a year that they spent with either a credit card payment 30 days delinquent or having reached 80% of their credit limit[15] and then averages that percentage across the geography.

"DQ30 and CL80 (last 6 years)" does the same over the last six years, calculating the portion of those quarters that an individual spent with either a credit card payment at least 30 days delinquent or having reached 80% of their available credit, and averaging this portion across all individuals in the sample from a given geography. In order to avoid bias in this metric, we require that an individual be in the sample for the entirety of those six years in order to be counted.

Given that our sampling method over samples the smallest zip codes, we weight the aggregation of these four financial distress statistics to the county level by the number of households in each zip code.

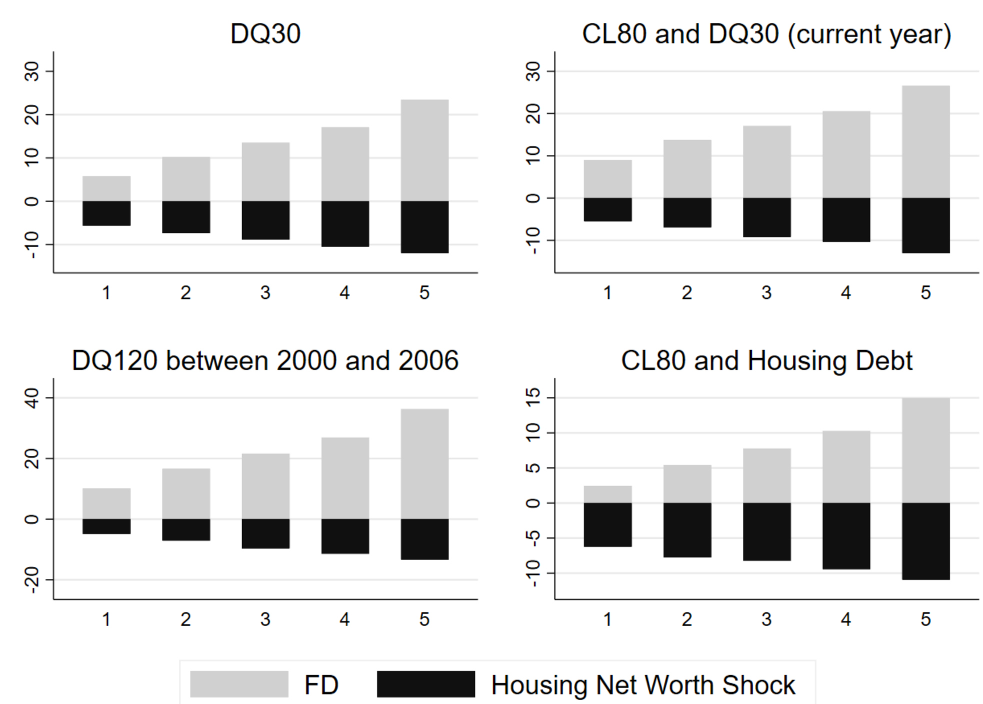
A.2 Correlation between FD and the Housing Wealth Shock

The motivating correlation between CL80 and the housing wealth shock of 2006-09 is robust to alternative definitions of financial distress, as can be seen in Figure 13. "DQ120 between 2000 and 2006" refers to the percent of people in a zip code who were 120 days or more delinquent on credit card payments at least once between 2000 and 2006. "CL80 and Housing Debt" gives the percentage of people in a zip code with both credit card debt at least 80% of their credit limit and debt indicative of owning a house, be that

[15] To give a clarifying example, say that there was an individual who in quarter 1 of 2006 was both at least 30 days delinquent on a credit card payment and had used over 80% of their available credit card credit. Then, in quarter 2, they remained over 80% of their credit card limit but did not have any credit card payments over 30 days delinquent. The rest of the year occurred without any credit incident. On our metric, this individual would have spent 50% of the year in financial distress. Similar calculations would be made for all other individuals in our sample from his or her geography, and those numbers would be averaged to reach the final result.

a mortgage or home equity line of credit. The levels of FD change depending on the definition, but the corresponding pattern in the housing net worth shock is immediately apparent in every case.

Figure 13: Correlation between the Housing Wealth Shock and FD under Alternate definitions of FD.



Notes: "FD" quintile means are weighted by the number of households in each zip code as of 2006, and "housing net worth shock" quintile means are weighted by 2006 net wealth.

A.3 Regression

The first-stage OLS regression for Table 8 is provided in Table 10. As explained previously, Saiz's measure of the elasticity of housing supply is used as an instrument to identify exogenous variation in home value. For robustness, Table 11 presents an OLS regression using the same functional form as Table 10. We have also computed the two-stage least squares regression using the Lutz and Sand [2017](LS) update of Saiz's housing price elasticity measure. This provided for more observations, 1074, and did not change the results.

It may be worried that there is another variable correlated with our measures of FD that better summarizes a households' financial condition. However, our measures of FD seem to do as well or better in this respect than other likely candidates. Iteratively controlling for the interaction between the change in home values and the homeownership percentage, age, education, the unemployment rate, or average household leverage leaves our results unchanged. The housing leverage ratio in particular is frequently suggested as a possible source of error, so Figure 12 directly compares our baseline to the results controlling for leverage, and Table 12 shows the corresponding regression output.

Our results are also robust to varying methods for calculating the financial wealth and housing shocks. MRS13 note that their method of calculating the change in financial wealth assumes that every household holds the market index of stocks and bonds. This assumption had to be made in their case because the IRS SOI data had not been released from 2009 at the time that their paper was written. Now, however, those data have been released, and we can calculate the change in FW directly for each geography i as $FW^i_{09} - FW^i_{06}$. Doing so does not change our results.

Similarly, in our baseline results we follow MRS13 to calculate the change in home prices using the Core Logic price index defined at the zip code and county level. Instead calculating the price change as the difference between the Zillow median price in 2009 and 2006 does not alter our results.

B Simulated Shocks

B.1 Quantifying the Covariance and Timing Channels

In Section 4.1, we compare the consumption effects of housing shocks and income shocks in isolation with consumption in an economy where a housing shock occurred the period before an income shock. The goal is to identify what we have called a "timing effect," the additional consumption losses occurring because of the interaction of shocks across time. It is not immediately obvious how to make this comparison, however, and so here we make our method for doing so clear.

Table 10: First-Stage OLS Regression

	(1)	(2)	(3)	(4)
		Δ_{06-09} Home Value		
	b/se	b/se	b/se	b/se
Saiz Elasticity	26.324***	26.343***	26.341***	26.304***
	(2.96)	(2.96)	(2.96)	(2.96)
Δ_{06-09} Income	14.040***	14.593***	15.641***	13.899***
	(3.22)	(4.15)	(3.92)	(3.99)
Δ_{06-09} Income $\times$ DQ30 (current year)	-13.967			
	(14.35)			
Δ_{06-09} Income $\times$ CL80 (current year)		-12.948		
		(14.17)		
Δ_{06-09} Income $\times$ CL80 and DQ30 (current year)			-19.814	
			(16.28)	
Δ_{06-09} Income $\times$ CL80 and DQ30 (last 6 years)				-14.739
				(21.33)
Δ_{06-09} Financial Wealth	-0.790	-1.059	-1.088	-0.514
	(0.70)	(0.93)	(0.86)	(0.86)
Δ_{06-09} Financial Wealth $\times$ DQ30 (current year)	2.245			
	(3.70)			
Δ_{06-09} Financial Wealth $\times$ CL80 (current year)		3.475		
		(3.32)		
Δ_{06-09} Financial Wealth $\times$ CL80 and DQ30 (current year)			3.833	
			(3.97)	
Δ_{06-09} Financial Wealth $\times$ CL80 and DQ30 (last 6 years)				0.450
				(4.82)
dYxY	-0.000***	-0.000***	-0.000***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
dFWxY	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
dYxFW	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
dFWxFW	-0.000***	-0.000***	-0.000***	-0.000***
	(0.00)	(0.00)	(0.00)	(0.00)
Percent of Households that Own Homes, 2006	106.420**	80.435*	94.546**	98.560**
	(32.29)	(31.75)	(31.93)	(31.18)
DQ30	216.400			
	(181.27)			
CL80		19.566		
		(170.17)		
CL80 and DQ30 (current year)			174.526	
			(201.20)	
CL80 and DQ30 (last 6 years)				205.513
				(235.41)
Constant	-194.177***	-138.684**	-181.803***	-190.110***
	(41.91)	(53.57)	(49.99)	(47.99)
Observations	623	623	623	623
F	23.47	23.53	23.32	23.51

Table 11: Auto Spending, County-Level

	Dependent Variable: Δ_{06-09} Auto Spending \$000			
	(1)	(2)	(3)	(4)
	b/se	b/se	b/se	b/se
Δ_{06-09} Home Value	-0.097**	-0.120**	-0.112*	-0.120**
	(0.04)	(0.04)	(0.04)	(0.04)
Δ_{06-09} Home Value × DQ30 (current year)	0.855***			
	(0.17)			
Δ_{06-09} Home Value × CL80 (current year)		0.616***		
		(0.14)		
Δ_{06-09} Home Value × DQ30 and CL80 (current year)			0.786***	
			(0.17)	
Δ_{06-09} Home Value × DQ30 and CL80 (last 6 years)				1.020***
				(0.20)
Δ_{06-09} Income	-0.728*	-1.404***	-1.053**	-0.990**
	(0.32)	(0.38)	(0.36)	(0.37)
Δ_{06-09} Income × DQ30 (current year)	5.429***			
	(1.45)			
Δ_{06-09} Income × CL80 (current year)		6.435***		
		(1.35)		
Δ_{06-09} Income × DQ30 and CL80 (current year)			6.295***	
			(1.53)	
Δ_{06-09} Income × DQ30 and CL80 (last 6 years)				7.645***
				(2.04)
Δ_{06-09} Financial Wealth	0.334***	0.417***	0.345***	0.280**
	(0.08)	(0.10)	(0.10)	(0.10)
Δ_{06-09} Financial Wealth × DQ30 (current year)	-1.908***			
	(0.40)			
Δ_{06-09} Financial Wealth × CL80 (current year)		-1.597***		
		(0.35)		
Δ_{06-09} Financial Wealth × DQ30 and CL80 (current year)			-1.655***	
			(0.43)	
Δ_{06-09} Financial Wealth × DQ30 and CL80 (last 6 years)				-1.691**
				(0.52)
Percent of Households that Own Homes, 2006	7.406*	8.694**	8.186*	10.383**
	(3.29)	(3.26)	(3.28)	(3.22)
DQ30	-73.860***			
	(18.56)			
CL80		-69.113***		
		(17.23)		
DQ30 and CL80 (current year)			-71.589***	
			(20.54)	
DQ30 and CL80 (last 6 years)				-70.408**
				(24.29)
Constant	5.881	10.182	7.410	3.571
	(4.37)	(5.45)	(5.17)	(5.06)
Observations	1083	1083	1083	1083

Note: Regressions are weighted by the number of owner-occupied housing units in each County in 2006. Additional controls not shown here include interactions between the levels and changes in housing wealth, income, and financial wealth.

Table 12: Auto Spending at the County-Level Controlling for Leverage (IV)

	Δ_{06-09} Auto Spending			
	(1)	(2)	(3)	(4)
	b/se	b/se	b/se	b/se
Δ_{06-09} Home Value	-0.058	-0.273*	-0.152	-0.096
	(0.11)	(0.13)	(0.13)	(0.13)
Δ_{06-09} Home Value × DQ30 (current year)	1.107*			
	(0.44)			
Δ_{06-09} Home Value × CL80 (current year)		1.509***		
		(0.39)		
Δ_{06-09} Home Value × CL80 and DQ30 (current year)			1.361**	
			(0.49)	
Δ_{06-09} Home Value × CL80 and DQ30 (last 6 years)				1.268*
				(0.58)
Δ_{06-09} Home Value × Housing Leverage Ratio	-0.241**	-0.203*	-0.220*	-0.238**
	(0.09)	(0.09)	(0.09)	(0.09)
Housing Leverage Ratio, 2006	19.940	72.274*	46.834	28.291
	(28.80)	(36.41)	(35.80)	(36.95)
Hou. Leverage Ratio, 2006 × DQ30 (current year)	-159.518			
	(137.46)			
Hou. Leverage Ratio, 2006 × CL80 (current year)		-318.021*		
		(135.79)		
Hou. Leverage Ratio, 2006 × CL80 and DQ30 (current year)			-264.291	
			(161.99)	
Hou. Leverage Ratio, 2006 × CL80 and DQ30 (last 6 years)				-171.738
				(194.17)
DQ30 (current year)	-23.770			
	(87.90)			
CL80 (current year)		57.944		
		(79.66)		
CL80 and DQ30 (current year)			14.773	
			(97.78)	
CL80 and DQ30 (last 6 years)				-11.671
				(119.99)
Percent of Households that Own Homes, 2006	-2.699	-2.272	-2.569	0.036
	(6.88)	(5.96)	(6.31)	(6.34)
Constant	7.445	-9.676	0.315	0.240
	(21.27)	(22.75)	(23.82)	(25.25)
Observations	623	623	623	623

Notes: regressions are weighted by the number of owner-occupied housing units in each county in 2006. Additional controls not shown here include the change in income, the change in financial wealth, and interactions between changes and levels for income, financial wealth, and housing wealth. The changes in income and financial wealth are also interacted with leverage.

Figure 14: Decomposition of a Housing Shock Covarying with β followed by an Income Shock

Figure 14 plots the log difference in aggregate consumption relative to the steady state under varying shock possibilities. The average percentage change in consumption for a covarying housing shock followed by an income shock is given by $^{(F+G+H)}/_3$. To compare this with the two shocks in isolation, we take their average percentage changes in consumption over the same three periods and add them together: $^{(A+B+C)}/_3 + {}^{(D+E)}/_3$. Through the timing effect, $^{(F+G+H)}/_3 > {}^{(A+B+C+D+E)}/_3$, as shown in the last panel of the figure. An analogous calculation is made to find the timing effects behind a uniform housing shock followed by an income shock.

B.2 Income Shocks

In Table 6, it was shown that being in FD increases an agent's responsiveness to changes in housing wealth. This also holds true during income shocks, as

Table 13: Heterogenous Response to Income Shock

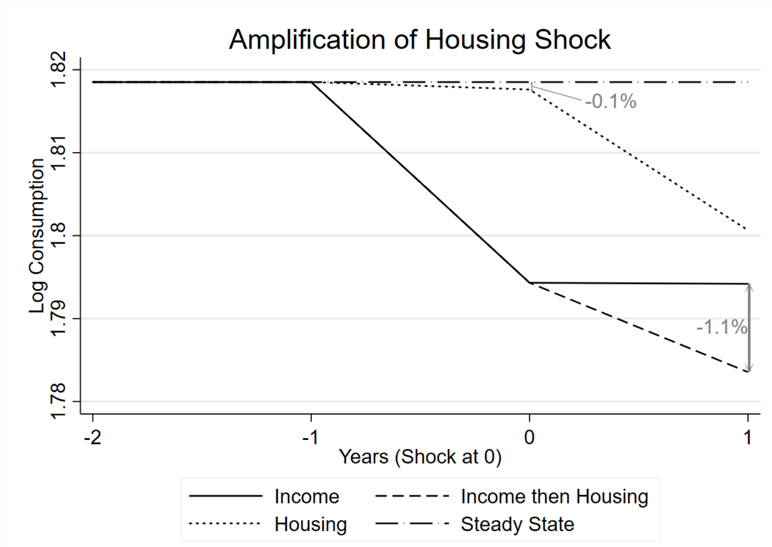
FD Group	% Change C Year of	Av. % Change	share pop	share low beta	FD Shock
Full Economy					
Total	-2.47	-2.45	100.00	32.00	13.81
Homeowners in Year of Shock					
Total	-2.75	-2.64	78.15	26.00	9.26
High FD	-2.81	-2.94	5.74	93.89	26.27
Low FD	-3.08	-2.99	18.66	74.86	27.16
No FD	-2.57	-2.42	53.75	1.78	1.23
Nonhomeowners in Year of Shock					
Total	0.12	-0.69	21.85	53.04	30.09
High FD	-2.37	-2.51	10.51	99.57	56.06
Low FD	-1.96	-1.81	1.80	61.21	37.10
No FD	5.11	2.84	9.53	0.14	0.10

Notes: The "No FD" group includes individuals that have not been in FD for the last six time periods. Among those with some FD over the last six time periods, the 50th percentile of time spent in FD was found, and agents were divided into "high" and "low" FD based upon that threshold. Note that because this grouping is done based on the last six time periods, agents who have been in the model for fewer than six periods are omitted

we now show in the analogous Table 13. Cho et al. [2019] find something similar empirically, namely, that the consumption responses of households to income shocks are increasing in household debt. They provide the intuition that interest payments on debt form "consumption commitments" that are costly to adjust, and so households respond by cutting consumption that is not committed in this way more than would otherwise be expected. In our model, being already in FD when a shock hits further limits households' ability to alter such consumption commitments and amplifies the effect of the shock on consumption that is not committed.

What is more, just as Section 4.1 showed that a housing shock can amplify the effect of a subsequent income shock, an income shock can amplify the effect of a subsequent housing shock. Figure 15 shows that the effect of a uniform housing shock on consumption in the year that it occurs is over 10 times as pronounced when coming after an income shock.

Figure 15: Income Shocks Amplify the Effect of Subsequent Housing Shocks



Note: This graph plots the aggregate consumption changes under a variety of shock combinations. An initial income shock is applied at year zero. Then, in the "Income then Housing" line, a uniform housing shock is applied to the economy in year 1.

C Recursive formulation of model

C.1 Nonhomeowner

If the household of type j does not own a house, it must decide whether or not to default on its financial asset/debt holdings a and whether to stay as a renter R or buy a house B. Given these two decisions, we can write the lifetime utility of a household in this situation as:

$$N_{j,n}(a,z,\epsilon) = \max_{I_{rent}\in\{0,1\}} \left\{ I_{rent} R_{j,n}(a,z,\epsilon) + (1-I_{rent}) B_{j,n}(a+e_n(z,\epsilon),z) \right\}. \quad (6)$$

where earnings are $e_n(z,\epsilon) = exp(f + l_n + z + \epsilon)$. Here I_{rent} equals one when the household choose to rent, R is the lifetime value of renting, and B is the lifetime value of buying a house. These value functions take the form of:

$$R_{j,n}(a,z,\epsilon) = \max \left\{ R^P_{j,n}(a,z,\epsilon), R^{BK}_{j,n}(a,z,\epsilon), R^{DQ}_{j,n}(a,z,\epsilon) \right\}, \quad (7)$$

and

$$B_{j,n}(a,z,\epsilon) = B^P_{j,n}(a,z,\epsilon). \quad (8)$$

Notice that households that purchase a house are not allowed to default (in any form) on credit card debt, so the last equality is only for expositional clarity. The super scripts in each value function represent whether the household is defaulting or not on financial assets. We describe these problems next.

Renter and no financial asset default. A household that is a renter and decides not to default on financial assets can only choose next period's financial assets a':

$$\begin{aligned} R^P_{j,n}(a,z,\epsilon) = \max_{a'} \quad & u(c,h_R) + \beta_j E\Big[N_{j,n-1}(a',z',\epsilon')|z\Big] \quad (9) \\ s.t. \quad & c + q^a_{j,n}(h_R,0,a',z)a' = e + a, \\ e \quad = \quad & exp(f + l_n + z + \epsilon). \end{aligned}$$

Here q^a is the price of borrowing financial assets, which depends on housing, income states, and discount factor type j.

Renter and bankruptcy. A household that is a renter and decides to formally default on financial assets a solves the following trivial problem:

$$R^{BK}_{j,n}(a,z,\epsilon) \;=\; u(c,h_R)+\beta_j E\Big[N_{j,n-1}(0,z',\epsilon')|z\Big] \tag{10}$$

$$s.t. \qquad c = e - (\text{filing fee}),$$

$$e \;=\; exp(f+l_n+z+\epsilon).$$

Here, filing fee is the bankruptcy filing fee.

Renter and delinquency. A household that is a renter and decides to skip payments (i.e., become delinquent) on financial assets a solves the following trivial problem:

$$R^{DQ}_{j,n}(a,z,\epsilon) \;=\; u(c,h_R)+\beta_j E\Big[\gamma N_{j,n-1}(0,z',\epsilon')+(1-\gamma)N_{j,n-1}(a(1+r^R),z',\epsilon')|z\Big] \tag{11}$$

$$s.t. \qquad c = e,$$

$$e \;=\; exp(f+l_n+z+\epsilon).$$

Here, γ is the probability of discharging delinquent debt, and r^R is the roll-over interest rate on delinquent debt.

Homebuyer. A household of type j that is buying a house and has cash in hand a must choose next period's financial assets a', the size of their house h', and the amount to borrow in the mortgage for the house m'.

To simplify the problem later, consider a individual choosing to buy a house of size $h' \in \{h_1.....,h_m\}$,

$$\hat{B}_{j,n}(a,z;h') = \max_{a',m'} \qquad u(c,h')+\beta_j E\Big[H_{j,n-1}(h',m',a',z',\epsilon')|z\Big] \tag{12}$$

$$s.t. \;\; c+q^a_{j,n}(h',m',a',z)a' = \quad a+q^m_{j,n}(h',m',a',z)m' - I_{m'>0}\xi_M-(1+\xi_B)ph',$$

$$q^m_{j,n}(h',m',a',z)m' \leq \lambda ph'.$$

Here, q^m is the price of borrowing m' for a house, which depends on house size, income states, and discount factor type j. The other constraints reflect a loan-to-value constraint and that houses must come in discrete sizes. With this notation, the problem of a homebuyer is simply

$$B_{j,n}(a,z) = \max_{h' \in \{h_1,\ldots,h_H\}} \hat{B}_{j,n}(a,z;h'). \tag{13}$$

Notice that in the case of the renter the cash on hand is simply financial assets plus earnings. Below, we will use the same value function B for individuals in different situations (e.g., moving from one house to another).

C.2 Homeowner

The homeowner's problem is more complex. On the financial asset dimension, homeowners must decide to default or repay their financial assets. On the housing dimension, homeowners can : (i) pay their current mortgage (if any), (ii) refinance their mortgage (or ask for a mortgage if their don't have one), (iii) default on their mortgage, (iv) sell their house and buy another one, or (v) become a renter. The value function H is given by the maximum of:

$$H_{j,n}(h,m,a,z,\epsilon) = \max\left\{ P_{j,n}(\cdot), F_{j,n}(\cdot), D_{j,n}(\cdot), S^B_{j,n}(\cdot), S^R_{j,n}(\cdot) \right\} \tag{14}$$

where:

$$P_{j,n}(h,m,a,z,\epsilon) = \max\left\{ P^P_{j,n}(\cdot), P^{BK}_{j,n}(\cdot), P^{DQ}_{j,n}(\cdot) \right\}, \tag{15}$$

$$F_{j,n}(h,m,a,z,\epsilon) = F^P_{j,n}(\cdot), \tag{16}$$

$$D_{j,n}(h,m,a,z,\epsilon) = \max\left\{ D^P_{j,n}(\cdot), D^{BK}_{j,n}(\cdot), D^{DQ}_{j,n}(\cdot) \right\}, \tag{17}$$

$$S^B_{j,n}(h,m,a,z,\epsilon) = S^{B,P}_n(\cdot), \tag{18}$$

$$S^R_{j,n}(h,m,a,z,\epsilon) \quad = \quad S^{R,P}_n(\cdot). \tag{19}$$

Notice that households that choose to refinance their mortgage cannot default on financial assets in any way. Additionally, sellers must also pay their financial assets.

Mortgage payer and no financial asset default. Households that decide to pay their mortgage and their financial assets have the following problem:

$$\begin{aligned} P^P_{j,n}(h,m,a,z,\epsilon) \quad &= \quad \max_{a'} \ u(c,h) + \beta_j E\Big[H_{j,n-1}(h',m(1-\delta),a',z',\epsilon')|z\Big] \\ s.t. \qquad & c + q^a_{j,n}(h,m(1-\delta),a',z)a' = e + a - m, \\ & e = exp(f + l_n + z + \epsilon). \end{aligned} \tag{20}$$

Mortgage payer and bankruptcy. Households that decide to pay their mortgage but formally default on their financial assets have the following (trivial) problem:

$$\begin{aligned} P^{BK}_{j,n}(h,b,a,z,\epsilon) \quad &= \quad u(c,h) + \beta_j E\Big[H_{j,n-1}(h',m(1-\delta),0,z',\epsilon')|z\Big] \\ s.t. \qquad & c = e - \text{filing fee} - m, \\ & e = exp(f + l_n + z + \epsilon). \end{aligned} \tag{21}$$

Mortgage payer and delinquency. Households that decide to pay their mortgage but informally default on their financial assets have the following (trivial) problem:

$$\begin{aligned} P^{DQ}_{j,n}(h,m,a,z,\epsilon) \quad &= \quad u(c,h) + \beta_j E\Big[\gamma H_{j,n-1}(h',m(1-\delta),0,z',\epsilon') \\ & \quad +(1-\gamma)H_{j,n-1}(h',m(1-\delta),a(1+r^R),z',\epsilon')|z\Big] \\ s.t. \qquad & c = e - m, \\ & e = exp(f + l_n + z + \epsilon). \end{aligned} \tag{22}$$

Mortgage refinancer. A household that is a house refinancer cannot default on financial assets a and must prepay its current mortgage, choose next period's financial assets a', and choose the amount to borrow m' with their new mortgage:

$$F^{P}_{j,n}(h,m,a,z,\epsilon) = \hat{B}_{j,n}(a + ph(1+\xi_B) - q^*_n m + e_n(z,\epsilon), z; h) \tag{23}$$

Note, this problem is just a special case of a homebuyer who is "rebuying" their current home of size h, but now has cash-on-hand equal to earnings plus financial assets minus fees from prepaying the previous mortgage m. Also note that $ph(1+\xi_B)$ is simply an adjustment so the household doesn't actually pay adjustment costs of "rebuying" their current home.

Mortgage defaulter and no financial asset default. A household that defaults on its mortgage and chooses not to default on its financial assets a immediately becomes a renter and must choose next period's financial assets a'. Importantly, since we assume the cost of defaulting on your mortgage is a utility cost Φ, we can easily write this problem as the problem of a renter minus the utility cost of mortgage default:

$$D^{P}_{j,n}(h,m,a,z,\epsilon) = R^{P}_{j,n}(a,z,\epsilon) - \Phi. \tag{24}$$

Mortgage defaulter and bankruptcy. Using the same trick as above, we can write the problem as a mortgage defaulter who chooses bankruptcy (on financial assets) as the problem of a renter who files for bankruptcy:

$$D^{BK}_{j,n}(h,m,a,z,\epsilon) = R^{BK}_{j,n}(a,z,\epsilon) - \Phi. \tag{25}$$

Mortgage defaulter and delinquency. Lastly, we can write the problem as a mortgage defaulter who chooses delinquency (on financial assets) as the problem of a renter who is delinquent on existing debt:

$$D^{DQ}_{j,n}(h,m,a,z,\epsilon) = R^{DQ}_{j,n}(a,z,\epsilon) - \Phi. \tag{26}$$

Seller to renter. Note that a seller who decides to rent (and not default on financial assets) is simply a renter with financial assets equal to a plus the gains/losses from selling their current house.

$$S^{R,P}_{j,n}(h,m,a,z,\epsilon) = R^{P}_{j,n}(a + ph(1-\xi_S) - q^*_n m, z, \epsilon) \tag{27}$$

Seller to other house. This problem is just a special case of a home-buyer with cash on hand equal to earnings plus current financial assets plus gains/losses from selling the previous house.

$$S^{P,B}_{j,n}(h,m,a,z,\epsilon) = B_{j,n}(a + ph(1-\xi_S) - q^*_n m + e_n(z,\epsilon), z). \tag{28}$$

C.3 Mortgage prices

When a household asks for a mortgage that promises to pay m' next period, the amount it borrows is given by $m' q^m_n(h',m',a',z)$, where:

$$q^m_{j,n}(h',m',a',z) = \frac{q^m_{pay,j,n} + q^m_{prepay,j,n} + q^m_{default,j,n}}{1+r}. \tag{29}$$

First, consider the price of payment tomorrow, q_{pay}

$$\begin{aligned} q^m_{pay,j,n}(h',b',a',z) &= \\ &\rho_n E\Big[\text{mort pay, no def} + \text{mort pay, BK} + \text{mort pay, DQ}\Big| z\Big], \end{aligned} \tag{30}$$

with:

$$\begin{aligned} \text{mort pay, no def} &= I_{P^P_{j,n-1}(h',m',a',z',\epsilon')}\Big[1 + (1-\delta) q^m_{j,n-1}(h',m'',a'',z')\Big], \\ a'' &= \hat{a}^{P,P}_{j,n-1}(h',m',a',z',\epsilon'), \end{aligned} \tag{31}$$

$$\text{mort pay, BK} = I_{P^{BK}_{j,n-1}(h',m',a',z',\epsilon')}\Big[1 + (1-\delta) q^m_{n-1}(h',m'',0,z')\Big], \tag{32}$$

and

$$\begin{aligned} \text{mort pay, DQ} &= I_{P^{DQ}_{j,n-1}(h',m',a',z',\epsilon')}\Big[1 + (1-\delta) \times \\ &\Big(\gamma q^m_{j,n-1}(h',m'',0,z') + (1-\gamma) q^m_{j,n-1}(h',m'',a'',z')\Big)\Big], \end{aligned} \tag{33}$$

with: $\quad a'' = (1+r^R)a'$ and $m'' = m'(1-\delta)$.

Here, ρ_n is the age-specific survival probability, and I equals 1 whenever the corresponding value function is the maximum of $P_{j,n-1}$.
Next, consider the price of pre-payment tomorrow, q_{prepay}. This occurs when

the household chooses to refinance their current house, or when they choose to sell their current house. Importantly, in either case (and regardless of what the household chooses to do immediately after selling their current house) creditors receive value q^*:

$$\begin{aligned} q^m_{prepay,j,n}(h',m',a',z) \;=\; & \\ & E\Big[\Big(I_{F_{j,n-1}(h',m',a',z',\epsilon')} \\ & +I_{S^R_{j,n-1}(h',m',a',z',\epsilon')} + I_{S^B_{j,n-1}(h',m',a',z',\epsilon')}\Big)q^*_{j,n-1}\Big|z\Big]. \end{aligned} \tag{34}$$

Finally, consider the price of defaulting on the mortgage tomorrow, $q_{default}$. Creditors recover $ph'(1-\bar{\xi}_S)$. So, the price of default is simply:

$$\begin{aligned} q^m_{default,j,n}(h',m',a',z) \;=\; & \\ & \rho_n E\left[\frac{\Big(I_{D_{j,n-1}(h',m',a',z',\epsilon')}\Big)ph'(1-\bar{\xi}_S)}{m'}\Bigg|z\right]. \end{aligned} \tag{35}$$

C.4 Bond prices

When a household issues debt and promises to pay a' next period, the amount it borrows is given by $a'q^a_n(h',b',a',z)$, where:

$$q^a_{j,n}(h',m',a',z) \;=\; \frac{q^a_{pay,j,n}+q^a_{DQ,j,n}}{1+r}. \tag{36}$$

First, consider the price of payment tomorrow, q^a_{pay}. This occurs in the following states: renter, no financial asset default; homebuyer, no financial asset default; mortgage payer, no financial asset default; mortgage refinancer, no financial asset default; mortgage defaulter, no financial asset default; seller to renter; and seller to buyer. In all of these cases creditors get paid the same amount per unit of debt issued by the household. Thus,

$$
\begin{aligned}
q^a_{pay,j,n}(h',m',a',z) = \rho_n E\Bigg[\quad & I_{R^P_{j,n-1}(a',z',\epsilon')} + I_{B_{n-1}(a'+e_{n-1}(z',\epsilon'),z',\epsilon')} && (37)\\
& + I_{P^P_{j,n-1}(h',m',a',z',\epsilon')} + I_{F^P_{j,n-1}(h',m',a',z',\epsilon')} \\
& + I_{D^P_{j,n-1}(h',m',a',z',\epsilon')} \\
& + I_{S^{R,P}_{j,n-1}(h',m',a',z',\epsilon')} + I_{S^{B,P}_{j,n-1}(h',m',a',z',\epsilon')} \Bigg| z \Bigg].
\end{aligned}
$$

Notice that the first two terms of the expectation can only occur if $h' = h_R$, whereas the latter five only occur if $h' > h_R$. Additionally, the first default term is unnecessary since mortgage default never occurs without the depreciation shock when house prices are constant.

Next, consider the price given delinquency tomorrow, q^a_{DQ}. This occurs in three states: renter, delinquency; mortgage payer, delinquency; and mortgage defaulter, delinquency. In all of these cases debt gets rolled over at a rate $(1+r^R)$ with probability $(1-\gamma)$. However, tomorrow's price of this rolled-over debt varies by state. Thus,

$$
\begin{aligned}
q^a_{DQ,j,n}(h',m',a',z) = (1-\gamma)(1+r^R)\rho_n E\Bigg[& I_{R^{DQ}_{j,n-1}(a',z',\epsilon')} \times q^a_{j,n-1}(h_R,0,a'',z') && (38)\\
& + I_{D^{DQ}_{j,n-1}(h',m',a',z',\epsilon')} \times q^a_{j,n-1}(h_R,0,a'',z') \\
& + I_{P^{DQ}_{n-1}(h',b',a',z',\epsilon')} \times q^a_{j,n-1}(h',m'',a'',z')|z \Bigg] \\
\text{with: } & a'' = (1+r^R)a' \qquad \text{and } \; b'' = b'(1-\delta).
\end{aligned}
$$

Notice here too that the first term can only occur if $h' = h_R$, whereas the latter two only occur if $h' > h_R$.