Financial Distress and Macroeconomic Risks

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"Household Financial Distress and the Burden of "Aggregate" Shocks"
Financial Distress and Macroeconomic Risks*

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Abstract
This paper investigates how, and how much, household financial distress (FD), arising from allowing debts to go unpaid, matters for the aggregate and cross-sectional consumption responses to macroeconomic risk. Through a battery of structural models, we show that FD can affect consumption responses through three channels: (1) as another margin of adjustment to shocks (direct channel); (2) because its persistence implies a significant degree of preference heterogeneity (indirect channel); and (3) because it can exacerbate macroeconomic risks whenever it is more severe in the hardest-hit regions, as evinced by the last two recessions (correlation channel). We find that all channels shape cross-sectional differences in the response of consumption to shocks. However, only the direct and indirect channels matter in the aggregate.

Keywords: Geography, Consumption, Credit Card Debt, Recession, Bankruptcy, Foreclosure, Mortgage, Delinquency, Financial Distress, Inequality, Poverty.

JEL Codes: D31, D58, E21, E44, G11, G12, G21

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1 Introduction

Although the conventional view in macroeconomics is concerned with aggregate consequences of recessions, we believe that fully gauging the impact of recessions demands moving beyond the aggregate change to consider the entire distribution of responses across households. This paper aims to investigate how household balance sheet vulnerability, or what we call financial distress (FD), matters for understanding the aggregate and cross-sectional consumption responses to macroeconomic shocks. FD may be an amplifier of aggregate shocks for at least three reasons. First, FD as a form of debt repudiation may matter directly as it allows for another margin of adjustment to insulate consumption from shocks. Second, as highlighted by previous work, at an individual level, FD is very persistent. Thus, from a modeling standpoint, it indirectly implies a significant degree of ex-ante heterogeneity across agents. Third, as we document below, regions of the United States that had, on average, higher FD were also regions that were the most exposed to the last two recessions. More specifically, FD prior to the Great Recession (GR) was positively correlated with large subsequent house-price declines. Meanwhile, FD prior to the COVID-19 (CV19) pandemic was also positively correlated with greater employment in leisure and hospitality and larger reported labor earnings losses. We refer in what follows to these as simply the direct, indirect, and correlation channels of FD.

To answer the question posed at the onset, we construct a structural model that disentangles FD’s quantitative importance through each channel. The model, which is an extension of a standard life cycle model of consumption and savings, allows for formal default (bankruptcy) and informal default via non-repayment (delinquency), the latter formalizing FD in our model. We structurally estimate critical parameters of the model to match the distribution of FD observed in the data. The empirics of FD suggest a significant degree of ex-ante heterogeneity in the population, which we capture in a parsimonious way. We then calibrate aggregate shocks in the model to mimic the observed positive correlation with FD in both the GR and CV19 pandemic and use the model as a laboratory to understand how FD and its channels matter for outcomes. We focus on three outcomes following an “aggregate” shock: (i) the response of aggregate consumption, (ii) the dispersion of consumption responses across the distribution of ex-ante FD, and (iii) the impact on the most disadvantaged households, measured by the change in consumption-based poverty. The first is a natural gauge of aggregate consequences, while the latter two outcomes highlight how FD may intensify the consequences of aggregate shocks to inequality and measures of relative

\[ ^{1}\text{An excellent summary of research about macroeconomics and household heterogeneity can be found in } \text{Krueger, Mitman, and Perri (2016).}\]

\[ ^{2}\text{See, for example, Athreya et al. (2019).}\]
deprivation. We also decompose how the three channels of FD shape each outcome.

Focusing first on house-price shocks, like those during the GR, we find that all channels are important, though in distinct ways. FD’s direct channel (as another margin of adjustment) amplifies the aggregate response of consumption and increases poverty. Both of these findings are the result of households, on average, being in worse financial shape when FD is an option compared to a counterfactual scenario when it is not. In contrast, the indirect channel (through the heterogeneity FD encodes) attenuates the aggregate response of consumption and decreases poverty. This reflects the fact that the ex-ante heterogeneity that FD captures implies that more financially fragile households are less likely to own houses. Next, along the distribution of ex-ante FD, the indirect channel is critical as it amplifies differences in the response of consumption between the most and least distressed. Lastly, while the correlation channel (regional FD is correlated with subsequent aggregate shock exposure) has no aggregate impact, it amplifies dispersion in the cross-section of FD and effectively increases poverty relative to our baseline model. This last finding reflects the fact that when house-price declines are correlated with FD, housing affordability rises the most in areas less able to benefit from it.

Turning to labor income shocks of the magnitude and distribution of those occurring during the CV19 pandemic, we find that FD here matters directly and indirectly. In contrast, the correlation channel’s importance is narrower. Through its indirect channel, FD amplifies the drop in aggregate consumption following an income shock, exacerbates differences in consumption responses across the distribution of FD, and increases poverty. The findings reflect the fact that the dispersion in preferences that FD implies generates greater responsiveness to income shocks at the individual level and in aggregate. The direct channel also matters, but quantitatively, its contribution is smaller compared to the indirect channel. Lastly, the correlation channel’s importance is narrower as it amplifies dispersion in responses in the cross-section but does not affect the two other outcomes we analyze.

Our conclusions on the relative importance of direct versus indirect channels of FD have practical implications for the literature on “heterogeneity and the macroeconomy” more broadly. For questions regarding shocks to asset prices like house values, our results suggest that, while tedious, the specific modeling of FD as an endogenous choice matters. However, for other shocks like income shocks, the debt market arrangement matters less. Here, though, the informational content of the data on FD, through the degree of ex-ante heterogeneity it uncovers, is much more critical. This finding suggests our structural estimates may have broader use as they reflect fundamental differences across agents. Finally, we show that explicitly matching the correlation between FD and macroeconomic shocks matters for the cross-sectional distribution of consumption responses and for poverty.
Our conclusion on the lack of importance of the correlation channel of FD to the aggregate consumption change is of relevance, as a priori, one would expect that the positive correlation between FD and shocks would lead only to worse aggregate outcomes. However, our model suggests that the correlation channel is not critical for aggregate consumption as a quantitative matter. This result follows from the comparatively smaller consumption share of the most financially disadvantaged. That is, the effect of greater exposure to macroeconomic shocks among more vulnerable US households is essentially offset in the aggregate by the sizeable level of inequality present. Importantly, this conclusion holds for both episodes we examine even though very different shocks characterized them.

The remainder of the paper is structured as follows. Below we provide a brief literature review and motivating evidence of FD as a measure of vulnerability in the context of this literature. Section 2 provides further details on the correlation between FD and aggregate shocks during the past two recessions. Section 3 outlines the model of consumption, debt, and default. Section 4 discusses the model parameterization and estimation along with the calibration of the aggregate shocks. Section 5 validates the model against some external information on the responsiveness of consumption to shocks. Section 6 contains our main quantitative results, and Section 7 concludes.

1.1 Related literature

Given our interest in how FD, through its various channels, affects the transmission of shocks into consumption, our paper is strongly tied to several research strands in macroeconomics, which we discuss below.

Our examination of the direct channel of FD and its importance for understanding the response of consumption to house-price shocks is closely related to recent work aimed at understanding dynamics in the wake of house price movements. However, our work differs from this strand of the literature precisely because of the direct channel of FD; i.e. incorporating formal and informal default as alternative margins of adjustment in the financial asset market. Incorporating mortgage default and allowing for exogenous house prices follows Corbae and Quintin (2015) and Hatchondo, Martinez, and Sánchez (2015). More recently, Kaplan, Mitman, and Violante (2020a) also used a quantitative model with long-term mortgages and mortgage default. They consider a new driving force, the change in expected house-price growth, which helps in accounting for the joint evolution of house prices and consumption during the GR. Garriga and Hedlund (2017) use a housing-search model to show that an endogenous decline in housing liquidity amplifies the decline in consumption during the GR.

Athreya, Sánchez, Tam, and Young (2015, 2017) and Athreya, Mustre-del Río, and Sánchez (2019) allow for formal and informal default in the financial asset market but have no housing choice.
Berger, Guerrieri, Lorenzoni, and Vavra (2018) was the first paper to study how prices affect consumption in a heterogeneous-agent model with incomplete markets and liquidity constraints. They show how consumption responses depend on factors such as the level and distribution of debt, the size and history of house price shocks, and the level of credit supply. Critically, though, none of these papers allow for both FD in the financial asset market and default in the mortgage market. As we show, the additional margin of adjustment to shocks that FD allows (i.e. the \textit{direct} channel) is critical for our predictions following house-price shocks.

The analysis of the \textit{direct} channel of FD and how it affects the transmission of income shocks into consumption is related to a set of papers that emphasize the modeling of delinquency or bankruptcy and how it shapes macroeconomic fluctuations. The main difference between that literature and our work is that we consider other channels by which delinquency or bankruptcy shape aggregate responses. For example, while Herkenhoff and Ohanian (2012) and Herkenhoff (2013) emphasize the importance of default for the dynamics of unemployment, Auclert and Mitman (2019) examine how the default choice is amplified through the Keynesian channels of aggregate demand (via sticky prices and aggregate demands externalities). Viewed through the lens of our model, those papers focus on how the \textit{direct} channel of FD (as an alternative margin of adjustment) affects subsequent macroeconomic outcomes. Our contribution is to also analyze how the \textit{indirect} (through the ex-ante heterogeneity it encodes) and \textit{correlation} (because of its positive correlation with aggregate shocks) channels of FD affect subsequent macroeconomic outcomes.

The \textit{indirect} channel of FD is identified using information from households in the left-tail of the wealth distribution, which is a different approach compared to previous work that has mostly used the right-tail of the wealth distribution (Krusell and Smith, 1998). In this sense, our findings on the \textit{indirect} channel of FD are in line with Parker (2017), who notes a “main finding is that the majority of lack of consumption smoothing is predicted by a simple measure that can be interpreted as impatience.”

The identification of the \textit{indirect} channel of FD is also related to papers using individual-level data and structural models to identify preference heterogeneity more generally. Aguiar, Bils, and Boar (2020) find that both discount factor heterogeneity and heterogeneity in the intertemporal elasticity of substitution (IES) are necessary to generate the correct individual consumption responses to income shocks. Similarly, Calvet, Campbell, Gomes, and Sodini (2019) also finds support for heterogeneity in discount factors and the IES when looking at spending and savings patterns from Swedish households. Mustre-del Río (2015) finds that substantial dispersion in the disutility of work is needed to match dispersion in labor supply across individuals that cannot be explained by wage differences alone. Finally, Gregory,
Menzio, and Wiczer (2021) also find evidence of substantial heterogeneity across workers using data from the Longitudinal Employer-Household Dynamics (LEHD) dataset. Compared to those papers we show how data on FD and homeownership identify a correlation between discount factors and preference for homeownership that shapes the predictions of poverty in response to house-price shocks.

The correlation channel of FD we highlight is closely related to previous work documenting the relationship between shocks during recessions and prior conditions. Guvenen, Ozkan, and Song (2014) document the entire distribution of income losses across many recessions. Especially relevant to our work is their finding that income losses during a recession generally tend to be larger the lower a individual’s pre-recession income.

Focusing more narrowly on the CV19 and its correlation with FD, our paper is related to a rapidly emerging literature. Using a very different data source, Chetty, Friedman, Hendren, and Stepner (2020) show that early on in the pandemic, spending patterns declined sharply in sectors that require physical interaction, causing layoffs that were particularly severe among low-income employees. Also related, Kaplan, Moll, and Violante (2020b) document that individuals in vulnerable occupations have lower labor incomes and lower liquid wealth. Glover, Heathcote, Krueger, and Rull (2020) emphasize the different economic effects of the pandemic on young and old individuals. Overall, this emerging literature aligns with our interpretation that the CV19 crisis has disproportionately affected employment and earnings in areas with a higher incidence of FD.

2 Empirical evidence

2.1 Financial distress as a measure of vulnerability

In this section, we motivate household FD as a measure of financial vulnerability. We begin by defining FD and highlighting some prior work on its incidence and persistence. Then, we motivate its usefulness as a measure of vulnerability by showing how FD helps predict consumption changes in response to house-price shocks.

We make use of two main definitions of FD developed by Athreya, Mustre-del Río, and Sánchez (2019). The first of these, labeled DQ30, refers to a case when an individual has a credit card account at least thirty days delinquent at some point during the year. The second measure, labeled CL80, is a case when an individual has reached at least 80% of their credit limit over the same time interval.\footnote{Any other metrics for FD used within this paper as robustness checks are defined and discussed in appendix Section A.3}

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Either of these definitions of FD is easily measured, timely, and encompassing. They are easily measured because they are built on the New York Fed Consumer Credit Panel (NY FED-CCP), which contains credit reports for millions of Americans. They are timely because they are updated monthly and released a few days after the end of the month. These variables are encompassing because, unlike other measures, neither requires knowledge of the items on an individual’s balance sheets or of the prices needed to compute measures such as net worth or leverage. Moreover, even a near-perfect knowledge of household or individual net wealth may not accurately represent vulnerability. For example, individuals with low levels of net worth may not be constrained. By contrast, seeing an individual become significantly delinquent, or utilizing most, if not all unsecured credit, is more telling. It is unlikely, given the costs associated with these actions, that individuals are unconstrained. Directly related, Gross and Souleles (2002) use exogenous variation in credit line extensions to gauge the fraction who increase their debt in response (and hence can be viewed as constrained). They find (perhaps unsurprisingly) that those close to their limits increased borrowing by most. A consensus might be that roughly 20% are “constrained” either in terms of excess sensitivity to income or in terms of responses to survey questions. Recall that one of our definitions defines FD as close to liquidity constraints: a household is in FD if it has exhausted more than 80% of its credit limit.

Figure 1, taken from Athreya et al. (2019), shows why FD (measured as severe delinquency of 120+ days) is a valuable measure to look at given its relatively high incidence and very high persistence over the life cycle. The dots in this figure show that, on average, roughly 10% of all individuals find themselves in FD, regardless of age. All the other markers reveal that conditional on being in FD today, the likelihood of being in FD in the future is high. For example, the triangles show that conditional on FD today individuals have roughly a 30% probability of being in FD in four years. Given that across all age groups the unconditional probability of FD is roughly 10%, this means that FD today makes it three times more likely to be in FD in four years, compared to unconditionally.

Aside from being relatively common and very persistent, FD appears to be a valuable measure of vulnerability. For example, Figure 2 reveals an increasing relationship between county-level FD (again using the DQ30 measure) and MPCs. The MPCs plotted in this figure are out of housing shocks and are calculated similarly to Mian, Rao, and Sufi (2013) and Kaplan, Mitman, and Violante (2016) using new auto registrations as the measure of

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5Think of those in middle age who are beginning wealth accumulation for retirement or those financially assisted by relatives. 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 or consumption commitments.
Figure 1: The Incidence of Persistence of FD Over the Life Cycle

Source: Athreya et al. (2019). This figure plots the average probability of being in FD, defined as an individual having a credit card account 120 days or more delinquent at some point during the year.

For ease of exposition, we present the average MPCs for different quintiles of FD, ranging from lowest FD (Q1) to highest FD (Q5).

As can be seen by looking at the darker bars in Figure 2, the MPC out of housing shocks increases from less than 1 cent to over 2 cents between the least and most distressed households. For reference, the horizontal line represents the MPC estimated by Mian, Rao, and Sufi (2013). In general, our estimates are slightly smaller than theirs but within the range of estimates reported in Dupor, Mehkari, Li, and Tsai (2019). Significantly, as can be seen by the lighter bars in Figure 2, this finding holds even when we control for housing leverage: MPCs still rise from less than 1 cent to above 2 cents. That the result survives the inclusion of housing leverage suggests FD is a broader measure of vulnerability. Intuitively, FD status at any given time encodes information about past debt (non)repayment decisions, something not directly captured by current debt nor leverage. In this sense, FD may help identify households’ attitudes toward debt and repayment, which are crucial to determining the consumption response to shocks.

See appendix A.4 for details and robustness of this relationship.
Figure 2: Marginal Propensity to Consume Out of a Dollar Change in Home Prices by Quintile of DQ30 in 2002

Financial distress and its correlation with aggregate shocks

Having defined FD and shown its usefulness as an individual measure of vulnerability, this section provides additional details on the correlation between FD and aggregate shocks. First, we show that higher FD before the GR was associated with subsequently more significant house-price declines. Then, we show that FD before the CV19 pandemic was associated with higher shock exposure in two ways: higher employment shares in contact-sensitive sectors before the pandemic and more significant earnings losses during it. Overall, this suggests that beyond being a relevant measure of individual vulnerability, the distribution of FD across the United States may help us better understand the aggregate and distributional consequences of the past two recessions.

Starting with the GR, the left panel of Figure 3 shows that home values during this event declined the most in higher FD communities. By 2012, regardless of FD, median home prices declined on average by around 15% relative to their 2006 levels. However, home price declines in zip codes with higher FD were twice that, or worse in many cases.

Perhaps worst of all, households hardest hit were not diversified. Specifically, we find...
that households with high FD also tended to hold a larger share of their net wealth in their homes. This result implies that when losses are measured as a percentage of net wealth, home value losses are more strongly correlated with FD. In other words, the skewed distribution of home-price losses generated an even more heavily skewed distribution of net wealth losses for regions in higher FD. Appendix Section A.3.2 illustrates this relationship.

Much like during the GR, the economic consequences of the CV19 pandemic also appear to be correlated with FD. As shown in the right panel of Figure 3, there is a strong and consistent positive relationship between FD incidence at the zip code level (measured by the incidence of DQ30 in 2018) and the share of those areas workers employed in leisure and hospitality. A natural conjecture is that income losses among high FD areas have been more significant than those in low FD areas.

Survey evidence from Bick and Blandin (2021) does suggest that individuals in higher FD areas have been more adversely impacted during the CV19 pandemic. Combining our measures of FD at the zip code level with survey responses from Bick and Blandin (2021), we calculate the shares of individuals reporting: (i) no earnings losses (or some increase); (ii) earnings losses of 25%; or (iii) earnings losses of 50% or more, all relative to earnings in February 2020 (if employed).

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*Notes: FD is measured as DQ30, which is the share of individuals who are at least thirty days delinquent on a credit card at some point in a given year. For ease of viewing, the data have been divided into forty bins with respect to DQ30, and each dot represents the mean of that bin. In panel (a) each bin is weighted by the housing wealth in each zip code in that bin as of 2006. In panel (b) each bin is weighted by the number of households in each zip code included in the bin.*

7 We are highly appreciative of Alexander Bick and Adam Blandin for sharing their data with us.
The left panel of Figure 4 shows that throughout 2020, individuals living in the most distressed zip codes were consistently more likely to report significant earnings losses compared to individuals living in the least distressed zip codes. Again for expositional simplicity, we group individual responses based on the incidence of FD at the zip code level and focus on differences between individuals living in zip codes with the highest (Q5) and lowest (Q1) incidence of FD. As of December 2020, about 25% of individuals in the highest quintile of FD (Q5) reported earnings losses of at least 50%. In contrast, the comparable figure for individuals in the lowest FD quintile (Q1) is 15%. This gap in reporting severe earnings losses between Q1 and Q5 is entirely reflected in the incidence of reporting no earnings losses (or increases). As can be seen in the right panel of Figure 4, individuals in Q5 have systematically been less likely to report earnings staying the same or increasing. As of December 2020, about 70% of individuals in Q5 report earnings staying the same. In contrast, around 80% of individuals. Overall, these findings suggest that whether looking at employment in contact-sensitive sectors or actual reported losses, the economic burden of the CV19 pandemic appears to have fallen strongest on the most financially vulnerable.

3 A life-cycle model of housing and FD

Having documented the positive correlation of FD with aggregate shocks, our next question is whether FD matters for the transmission of these shocks to consumption. Given that FD is at least partially endogenous, answering this question requires a model of debt acquisition, debt repayment, and consumption decisions. We now lay out such a model. In subsequent

Graphs with all quintiles appear in the appendix.
sections, we deploy it to measure, via specific counterfactuals, the role of FD in the response of consumption to housing and income shocks, including a quantification of the importance of the positive correlation between initial FD and these shocks.

3.1 Agents, markets, and debt default

There is a continuum of finitely lived individuals who are risk averse and discount the future exponentially. All individuals face risk of death in each period and survive to the next period with probability \( \rho_t \), where \( t \) denotes age. Agents work for a finite number of periods, retire at age \( W \), and die with certainty at age \( T \) (conditional on reaching this terminal age). In what follows, \( n \) denotes periods left until the last period of life \( T \), and is naturally related to age by the relation \( n = T - t \).

All agents are subject to risk in their income \( y \) (specified below). Additionally, agents are allowed to differ in the rate at which they discount the future. Specifically, a share \( p_L \) of the population has a discount factor of \( \beta_L \), while the remaining share has a discount factor of \( \beta_H \geq \beta_L \).\(^9\)

With respect to markets, individuals have (limited) access to credit and each period choose nondurable consumption \( c \), housing \( h \), mortgages \( m' \), and financial assets (or debt) \( a' \). They may choose to obtain housing services through homeownership or by renting. In the parametrization section, we will allow for ex-ante differences in the taste for homeownership, which are perfectly correlated with the discount factor heterogeneity. This heterogeneity helps account for observed differences in homeownership across income categories in the United States, and in particular, homeownership differences by FD.

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 (owner-occupied) houses, agents borrow using mortgages \( m' \). Importantly, borrowing capacity in the mortgage market is endogenously given by a zero-profit condition on lenders due to the limited commitment of agents to repay mortgages.\(^10\)

If agents choose to save in the financial asset \( a > 0 \), they receive a risk-free rate \( r \). However, when agents borrow \( (a < 0) \), the discount price of their unsecured debt \( (q) \) depends on how much they borrow because debt may be repudiated. Debt repudiation can occur in one of two ways. First, the agent may cease payment. This option is known as delinquency (DQ) or informal default. Importantly, because with delinquency a household’s debt is

\(^9\)Heterogeneity in the discount factor is common in macroeconomics, at least since Krusell and Smith (1998). However, the modeling and the calibration of \( \beta \) heterogeneity here follows closely Athreya, Mustre-del Río, and Sánchez (2019).

\(^10\)Housing choices, mortgages, and foreclosures are modeled as in Hatchondo, Martínez, and Sánchez (2015).
not necessarily forgiven, we allow for a probabilistic elimination of debts, with an i.i.d. probability $\eta$. This tractably captures not only the absence of a formal elimination of the debt, but also the empirical reality that creditors periodically give up on collections efforts.

With probability $1 - \eta$, then, a household’s rolled-over debt is not discharged. 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 failed to repay as promised, their consumption equals income. Second, as in standard 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.

### 3.2 Nonhomeowners

The options faced by a nonhomeowner with assets $a$ and income $y$ are represented in Figure 5. First, they can choose to either rent or buy a house and become a homebuyer. If renting is chosen, the nonhomeowner must decide between the three options described below. There is a letter associated with each position in the tree, representing the notation we use for the value function associated with each choice. For example, the value function for a nonhomeowner with state variable $a$ and $y$ is $N$. For the sake of brevity, our formal description of this recursive problems is presented in appendix C.

Figure 5: Decision Tree of a Nonhomeowner

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1 Athreya, Sánchez, Tam, and Young (2017) analyze facts about informal default and introduced it to heterogeneous-agent models. Athreya, Sánchez, Tam, and Young (2015) use this model to study the effect of the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005.
3.2.1 Renting a house

A renter of discount factor type $j$ with income $y$ who decides to pay unsecured debt (or has positive financial assets) chooses the next period’s financial assets $a'$. Hence, the agent’s budget constraint reads

$$c + q^a_j(h_R, 0, a', y)a' = y + a.$$

Here, $y$ denotes income and $q^a$ denotes 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 depend on the agent’s state vector and hence on housing, income, and their discount factor type.

Instead, if that renter decides to formally default on unsecured debt $a$, she faces the following trivial budget constraint: $c = y - \text{(filing fee)}$, where the “filing fee” is the bankruptcy filing fee.

Finally, if that renter decides to skip payments (i.e., become delinquent) on unsecured debt $a$, they consume $c = y$ and will have financial assets tomorrow equal to

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

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

3.2.2 Buying a house

An agent buying a house must choose next period’s financial assets $a'$, the size of the house $h'$, and the amount to borrow for the house $m'$. This agent faces the following constraints:

$$c + q^a_j(h', m', a', y)a' = y + a + q^m_j(h', m', a', y)m' - I_{m' > 0} \xi_M - (1 + \xi_B)ph',$$
$$q^m_j(h', m', a', y)m' \leq \lambda ph'.$$

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 $\lambda$ of the value of the house.
3.3 Homeowners

The choices available to an existing homeowner are presented in Figure 6. A homeowner’s problem is more complex. On the financial asset dimension, homeowners must decide to default or repay their unsecured debt. On the housing dimension, homeowners can (i) pay their current mortgage; (ii) refinance their mortgage; (iii) default on their mortgage; (iv) sell their house and buy another one; or (v) become a renter. Each option and the associated budget constraint are discussed below.

**Figure 6:** Decision Tree of a Homeowner

- **P**, pay $m$
  - $P^P$, pay/save assets $a$
  - $P^{BK}$, default on $a$
  - $P^{DQ}$, become delinquent on $a$

- **F**, refinance $m$ for $m'$
  - Pay/save assets $a$

- **H**, homeowner with $(a, y, h, m)$
  - **D**, default on $m$ and rent $h_R$
    - $D^P$, pay/save $a$
    - $D^{BK}$, default on $a$
    - $D^{DQ}$, become delinquent on $a$
  - **S_R**, sell $h$ and rent $h_R$
    - Pay/save $a$
  - **S_B**, sell $h$
    - Choose $h'$ and $m'$; pay/save $a$
3.4 Making the mortgage payment

Agents repaying their mortgage who also decide to pay their unsecured debt face the following budget constraint:

\[ c + q_{j,n}^a(h, m(1 - \delta), a', y)a' = y + a - m. \]

Notice that the bond prices these agents face depend on house size \( h \), 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 \( \delta \) captures the rate at which mortgage payments decay, which may happen, for example, because there is inflation, and payments are fixed in nominal terms.

Agents who pay their mortgage but formally default on unsecured debt 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.

Similarly, households who decide to pay their mortgage but informally default on their unsecured debt consume \( c = y - m \) and have financial assets tomorrow equal to

\[ a' = \begin{cases} 
0, & \text{with prob. } \eta, \\
(1 + r^R)a, & \text{with prob. } 1 - \eta.
\end{cases} \]

3.4.1 Refinancing the mortgage

An agent who refinances cannot default on unsecured debt \( a \), 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:

\[ c + q_{j,n}^a(h', m', a', y)a' = y + a - q^*a m + q_{j,n}^m(h', m', a', y)m' - I_{m' > 0} \xi_M, \]
\[ q_{j,n}^m(h', m', a', y)m' \leq \lambda ph'. \]
Here, \( q_n^* \) is the value of prepaying a mortgage of size \( m \) with \( n \) remaining periods worth of payments, which is:
\[
q_n^* = \frac{1 - \left( \frac{1 - \delta}{1 + r} \right)^{n+1}}{1 - \frac{1 - \delta}{1 + r}}, \text{ for } n \geq 1.
\]

3.4.2 Foreclosing on the mortgage

An agent who defaults on her mortgage and chooses to pay her unsecured debt \( a \) 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:
\[
c + q_n^a(h_R, 0, a', y)a' = y + a.
\]

Using the same reasoning as above, we can write the problem of a mortgage defaulter who chooses bankruptcy on unsecured debt as the problem of a renter who files for bankruptcy. Thus, the budget constraint is simply \( c = y - \text{filing fee} \).

Lastly, we can write the problem of a mortgage defaulter who chooses delinquency as the problem of a renter who is also delinquent on existing debt. This means that consumption is given by \( c = y \), and financial assets tomorrow are equal to
\[
a' = \begin{cases} 
0, & \text{with prob. } \eta, \\
(1 + r^R)a, & \text{with prob. } 1 - \eta.
\end{cases}
\]

3.4.3 Selling the house

A home seller who decides to rent cannot default on financial assets. Hence, their optimization problem collapses to that of a renter with financial assets equal to \( a \) plus the gains from selling their current house. The agent’s budget constraint in this case reads:
\[
c + q_n^a(h_R, 0, a', y)a' = y + a + ph(1 - \xi_S) - q_n^* m.
\]

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.

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

\[
c + q^a_{j,n}(h', m', a', y)a' = y + a + ph(1 - \xi_S) - q^m_{i,n}(h', m', a', y)m' - I_{m' > 0}\xi_M - (1 + \xi_B)ph', \\
q^m_{j,n}(h', m', a', y)m' \leq \lambda ph'.
\]

3.5 Debt prices

The price of debt, or the interest rate, is determined by risk-neutral lenders that make zero expected discounted profits. In this section, we present the three main components of debt prices. The full specification of each of these (three) prices is in appendix C.

The price of a mortgage, \(q^m_{j,n}\), for an agent of type \(j\), with income \(y\), and financial wealth \(a'\), for the next period and that promises a payment of \(m'\), is given by:

\[
q^m_{j,n}(h', m', a', y) = q^a_{pay,j,n} + q^a_{pay,j,n} + q^a_{defaul,t,j,n},
\]

where \(r\) is the risk-free interest rate. 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. We don’t restrict agent choices at all in this regard, which makes our setting very flexible. 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, and as is consistent with our overall approach, mortgage default can occur alongside financial debt payment, default, or delinquency. Notice that under this formulation, mortgage prices fully internalize how financial asset positions today and tomorrow affect the probability of mortgage default.

We can express unsecured debt prices similarly. 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 they borrow is given by \(a'q^a_{j,n}(h', m', a', y)\), where:

\[
q^a_{j,n}(h', m', a', y) = \frac{q^a_{pay,j,n} + q^a_{defaul,t,j,n}}{1 + r}.
\]

First, consider the price of a payment tomorrow, \(q^a_{pay,j}\). Conditional on being a nonhomeowner, this occurs in two scenarios: the agent is a renter with no unsecured debt default or a homebuyer. Conditional on being a homeowner, payment occurs if the homeowner: (i) is a mortgage payer with no unsecured debt default; (ii) is refinancing the mortgage; (iii) is a
mortgage defaulter with no unsecured debt default; (iv) is selling the house to become renter; and (v) is selling the house to buy another house. Regardless of homeownership status, in these cases, creditors get paid the same amount per unit of debt issued by the household.

Next, consider the price given delinquency tomorrow, \( q_{DQ,j} \). Conditional on being a nonhomeowner, this occurs only when renters choose delinquency. Meanwhile, conditional on being a homeowner, this value occurs in two cases: when mortgage payers choose delinquency and when mortgage defaulters choose delinquency. In all of these cases, debt gets rolled over at a rate of \((1 + rR)\) with probability \((1 - \eta)\). Importantly, though, tomorrow’s price of this “rolled-over” debt will depend on the agent’s 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.

4 Model estimation and shock calibration

In this section we describe how we take the previously described model to the data. The first step is to ensure that our model generates the wide dispersion in FD that the data suggests. Next, we calibrate shocks that can be fed into the model so as to mimic the GR and CV19 pandemic.

4.1 Model estimation

In order to capture the large dispersion in FD documented in Section ?? while maintaining tractability, we estimate the model for five distinct economies or “regions”. Each region or economy captures a collection of zip codes that belong to a particular quintile of FD. By calculating key statistics (e.g., FD, income, wealth, homeownership rate, etc.), for each such region, we can independently discipline the primitive parameters of all five economies. The statistics we target for each economy are shown in Table [1]

By construction, FD is increasing across quintiles. In terms of the absolute levels of FD (as defined by DQ30), we see that it increases from 8.6 percent for households in quintile 1 (Q1) to nearly triple that (23.5 percent) in quintile 5 (Q5). This is a first and clear indication that households from different quintiles tend to hold quite different positions in their balance sheets.[12]

Naturally, FD is inversely related to various other measures of economic health, wealth, and human capital. Areas with high FD tended in 2002 to have lower income, net wealth,
Table 1: Descriptive Statistics by Quintile of DQ30 in 2002

<table>
<thead>
<tr>
<th>Quintiles of DQ30 in 2002</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wealth</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Income Per Household (HH) $000</td>
<td>91.75</td>
<td>65.26</td>
<td>53.51</td>
<td>46.22</td>
<td>39.86</td>
</tr>
<tr>
<td>Net Wealth Per HH $000, ages 25-55</td>
<td>358.5</td>
<td>216.0</td>
<td>164.5</td>
<td>127.1</td>
<td>88.12</td>
</tr>
<tr>
<td>Fin. Wealth Per HH $000, ages 25-55</td>
<td>321.9</td>
<td>201.4</td>
<td>154.6</td>
<td>123.4</td>
<td>83.00</td>
</tr>
<tr>
<td>Net Fin. Wealth Per HH $000, ages 25-55</td>
<td>224.0</td>
<td>128.1</td>
<td>95.00</td>
<td>72.71</td>
<td>42.13</td>
</tr>
<tr>
<td>Median Home Value $000</td>
<td>297.0</td>
<td>219.0</td>
<td>179.9</td>
<td>154.8</td>
<td>128.6</td>
</tr>
<tr>
<td><strong>Human Capital</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less Than High School</td>
<td>7.659</td>
<td>11.95</td>
<td>16.69</td>
<td>19.63</td>
<td>23.73</td>
</tr>
<tr>
<td>High School</td>
<td>19.70</td>
<td>24.78</td>
<td>26.82</td>
<td>27.99</td>
<td>29.23</td>
</tr>
<tr>
<td>College</td>
<td>72.64</td>
<td>63.27</td>
<td>56.49</td>
<td>52.37</td>
<td>47.04</td>
</tr>
<tr>
<td>Age</td>
<td>44.27</td>
<td>43.61</td>
<td>43.27</td>
<td>42.84</td>
<td>42.64</td>
</tr>
<tr>
<td><strong>Debt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent of HHs That Own a Home</td>
<td>76.30</td>
<td>71.93</td>
<td>68.76</td>
<td>64.25</td>
<td>61.69</td>
</tr>
<tr>
<td>Percent of HHs With Housing Debt</td>
<td>49.77</td>
<td>44.67</td>
<td>39.83</td>
<td>36.27</td>
<td>31.84</td>
</tr>
<tr>
<td>Housing Debt Per Home Owner $000</td>
<td>135.0</td>
<td>102.3</td>
<td>83.91</td>
<td>73.38</td>
<td>58.95</td>
</tr>
<tr>
<td>CC Debt Per Household $000</td>
<td>5.238</td>
<td>4.803</td>
<td>4.407</td>
<td>4.171</td>
<td>3.806</td>
</tr>
<tr>
<td>Housing Leverage</td>
<td>44.11</td>
<td>47.98</td>
<td>44.57</td>
<td>46.04</td>
<td>43.36</td>
</tr>
<tr>
<td><strong>Delinquency</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HHs With Housing Debt and in FD / HHs (in %)</td>
<td>5.910</td>
<td>8.555</td>
<td>10.82</td>
<td>13.32</td>
<td>19.46</td>
</tr>
<tr>
<td>HHs With Housing Debt / HHs in FD (in %)</td>
<td>33.31</td>
<td>30.72</td>
<td>28.37</td>
<td>26.90</td>
<td>25.99</td>
</tr>
<tr>
<td>Foreclosure Rate</td>
<td>1.520</td>
<td>1.812</td>
<td>2.239</td>
<td>2.579</td>
<td>3.335</td>
</tr>
<tr>
<td>Bankruptcy Rate</td>
<td>0.392</td>
<td>0.553</td>
<td>0.631</td>
<td>0.648</td>
<td>0.639</td>
</tr>
<tr>
<td>DQ30</td>
<td>8.566</td>
<td>12.11</td>
<td>14.92</td>
<td>17.83</td>
<td>23.54</td>
</tr>
</tbody>
</table>

Notes: Here, housing debt refers to a mortgage or home equity line of credit. Housing leverage is measured as housing debt divided by the total housing wealth in each geography. The number of households weights all means, except housing debt per homeowner, which is naturally weighted by homeowners. “Ages 25-55” signifies that for the corresponding rows, we used financial wealth aggregates from the SCF between 1998 and 2016 for individuals ages 25 to 55. This is done because elderly populations hold a large share of financial wealth, and our model economy is calibrated for individuals 25 to 55 years old.

and home values. Lower wealth in high FD areas prevents them from sustaining as much debt as their low FD counterparts, both in terms of housing debt and, perhaps more surprisingly, credit card debt. This lower credit card debt arises because despite zip codes with high FD using a larger proportion of their available credit, they also tend on average to have significantly lower credit limits. On the other side, zip codes with low FD can hold greater
credit card debt because of their higher credit limits. Thus, from an ex-ante perspective, they are better situated to weather financial losses. In terms of human capital, while less than half of individuals in the highest quintile of FD have a college degree, nearly three-quarters of all individuals in the lowest quintile of FD do.

Since we intend to look at the interaction between FD and housing shocks, and since those in high FD zip codes are somewhat less likely to own homes, it would be problematic if the differences in FD across zip codes are driven mainly by people who do not own homes. To examine this, we need to identify at the individual level homeownership and FD, something we cannot do directly within Equifax. To solve this issue, we proxy for homeownership within the Equifax data by using measures of debt indicating home ownership: whether an individual has either a mortgage or a home equity line of credit (housing debt).\footnote{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 percent with housing debt usually underestimates the percentage of households that own the home they live in by about a third.} The bottom panel of the table shows that when we consider the fraction of people identified to both own a home and be in FD, the resulting differences between quintiles are similar in magnitude to those of FD considered directly. Taken as a whole, this suggests that it is highly unlikely that the dispersion in FD is being driven by people who do not own homes.

In assigning parameters to each region, we proceed in two steps. First, we directly set values for a subset of the most “standard” parameters and impose that these are common to households across our notion of regions. Second, given these first-stage values, we estimate the remaining parameters so that the model-simulated data match the statistics mentioned above for each of the five regions.

### 4.1.1 Assigning first-stage parameters

Table\textsuperscript{2} collects the parameters set externally. A period in the model refers to a year. Agents 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. The initial distribution of net financial wealth-to-earnings are set to match the distribution of net financial wealth-to-earnings of 25-year-olds in the Survey of Consumer Finances between 1998 and 2016.

For time preference, we follow Athreya, Mustre-del Río, and Sánchez (2019) in assuming that agents can either discount the future relatively little (i.e., be “patient”) and have discount factor $\beta_H$, or discount it more significantly (i.e., be “impatient”) and use discount factor $\beta_L$. This heterogeneity allows the model to capture well the joint distribution of net financial wealth, delinquency (incidence and persistence), and bankruptcy. We set $\beta_H=1.00$
and $\beta_L = 0.80$, which is within the range of estimates in Athreya, Mustre-del Río, and Sánchez (2019) and also Aguiar, Bils, and Boar (2020). What remains to be determined is the share of people of type-$L$, $s_L$, which we pin down below in Section 4.1.2.

In terms of preferences for consumption and housing, we assume households experience utility with a constant elasticity of substitution:

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

where $\gamma$ denotes the risk aversion parameter, $\alpha$ governs the degree of intra-temporal substitutability between housing and nondurable consumption goods, and $\theta$ determines the expenditure share for housing. Following Hatchondo, Martinez, and Sánchez (2015), we set $\gamma$ to 2, $\alpha$ to 0.5, and $\theta$ to 0.11.

Since our model must match as well as possible the overall homeownership rate and the joint distribution of homeownership and FD, we assume that the size of rental houses $h^R$ differs by preference type. The size of rental houses for $L$-types is denoted as $h^R_L$ and the size of rental houses for $H$-types as $h^R_H$. Differences in these two parameters help capture differences in the utility of homeownership (or disutility of renting) across types in a succinct fashion. Given the combinations of homeownership rates and incidence of FD that the data display, our model implicitly requires a very high degree homeownership (near 100%) among patient types across all quintiles of FD. Thus, we set $h^R_H$ to a very low value and leave $h^R_L$ as a parameter to be determined below. Additionally, because median home value to income ratios do not vary dramatically across quintiles of FD, we set house prices constant across the five economies at $p = 3.3$. Given the sizes of houses for purchase, this value helps generate median home value to income ratios between 3.2 and 3.3 as observed in the data.

Next, following Livshits, MacGee, and Tertilt (2007), the penalty rate for delinquent debt is set at 20% annually, and the bankruptcy filing costs are at 2.8% of average income, or roughly $1,000.

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 as follows

$$z^i_{n,t} = z^i_{n,t-1} + \epsilon^i_{n,t}. $$
We assume $\epsilon_{n,t}$ and $e_{n,t}$ are normally distributed with variances $\sigma^2_\epsilon$ and $\sigma^2_e$, respectively. While the income process do not vary across quintiles of FD, the level of income does. We normalize the level of income across quintiles such that the level of income in the third quintile of FD is equal to 1. Given the income levels shown in Table I these normalizations imply that income in the first quintile of FD is about 40% larger than the third quintile. Meanwhile, income in the fifth quintile of FD is about 24% smaller than in the third quintile.

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: $\max\{A_0 + A_1 \exp(z_{W1}), A_2\}$. 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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Definition</th>
<th>Basis</th>
</tr>
</thead>
<tbody>
<tr>
<td>$l$</td>
<td></td>
<td>Life-cycle component of income</td>
<td>Kaplan and Violante (2010)</td>
</tr>
<tr>
<td>$W$</td>
<td>65</td>
<td>Retirement age</td>
<td>U.S. Social Security</td>
</tr>
<tr>
<td>$\rho_n$</td>
<td></td>
<td>Mortality age profile</td>
<td>Kaplan and Violante (2010)</td>
</tr>
<tr>
<td>$a_0$</td>
<td></td>
<td>Initial net financial asset distribution</td>
<td>SCF 1998-2016</td>
</tr>
<tr>
<td>$\sigma^2_\epsilon$</td>
<td>0.063</td>
<td>Variance of $\epsilon$</td>
<td>Kaplan and Violante (2010)</td>
</tr>
<tr>
<td>$\sigma^2_e$</td>
<td>0.0166</td>
<td>Variance of $e$</td>
<td>Kaplan and Violante (2010)</td>
</tr>
<tr>
<td>$r$</td>
<td>0.03</td>
<td>Risk-free rate</td>
<td>Standard</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>2</td>
<td>Risk aversion</td>
<td>Standard</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.5</td>
<td>Elasticity of substitution</td>
<td>Standard</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.11</td>
<td>Consumption weight of housing</td>
<td>Hatchondo, Martínez, and Sánchez (2015)</td>
</tr>
<tr>
<td>$\xi_B$</td>
<td>0.03</td>
<td>Cost of buying a house, households</td>
<td>Gruber and Martínez (2003)</td>
</tr>
<tr>
<td>$\xi_S$</td>
<td>0.03</td>
<td>Cost of buying a house, households</td>
<td>Gruber and Martínez (2003)</td>
</tr>
<tr>
<td>$\bar{\xi}_S$</td>
<td>0.22</td>
<td>Cost of selling a house, banks</td>
<td>Pennington-Cross (2006)</td>
</tr>
<tr>
<td>$\xi_M$</td>
<td>0.15</td>
<td>Cost of signing a mortgage</td>
<td>U.S. Federal Reserve</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.02</td>
<td>Payments decay</td>
<td>Average inflation</td>
</tr>
<tr>
<td>$A_0$</td>
<td>0.7156</td>
<td>Replacement ratio</td>
<td>U.S. Social Security</td>
</tr>
<tr>
<td>$A_1$</td>
<td>0.04</td>
<td>Replacement ratio</td>
<td>U.S. Social Security</td>
</tr>
<tr>
<td>$A_2$</td>
<td>0.14</td>
<td>Replacement ratio</td>
<td>U.S. Social Security</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>0.9</td>
<td>LTV limit</td>
<td>Positive down payment</td>
</tr>
<tr>
<td>$f$</td>
<td>0.028</td>
<td>Cost of filing for bankruptcy/mean(inc)</td>
<td>Livshits, MacGee, and Tertilt (2007)</td>
</tr>
<tr>
<td>$r_R$</td>
<td>0.2</td>
<td>Roll-over rate on delinquent debt</td>
<td>Livshits, MacGee, and Tertilt (2007)</td>
</tr>
<tr>
<td>$\beta_H$</td>
<td>1.00</td>
<td>Discount factor of patient types</td>
<td>Athreya, Mustre-del Río, and Sánchez (2019)</td>
</tr>
<tr>
<td>$\beta_L$</td>
<td>0.80</td>
<td>Discount factor of impatient types</td>
<td>Athreya, Mustre-del Río, and Sánchez (2019)</td>
</tr>
<tr>
<td>$h^R_H$</td>
<td>0.001</td>
<td>Size of rental house for patient types</td>
<td>See text</td>
</tr>
<tr>
<td>$p$</td>
<td>3.33</td>
<td>House prices</td>
<td>See text</td>
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</tbody>
</table>
4.1.2 Estimating the remaining parameters

The remaining parameters to be determined are (i) the share of impatient types in the population \( s_L \); (ii) the rental house size \( h^R_L \) for impatient types; and (iii) the probability of delinquent debt being fully discharged \( \eta \). We estimate these three parameters so that model replicates some critical features of the data on homeownership, financial wealth, and FD for each of the five regions we construct.

Table 3 presents the model’s fit for each of the quintile-specific moments. The model does a good job of matching differences in financial wealth across the five quintiles, though it cannot quite reproduce the extreme differences between Q1 and Q5. Additionally, it replicates the fact that homeownership declines as FD rises and matches the share of individuals in FD that have housing debt well. Because most individuals in FD who own a home will tend to have mortgages or home equity lines of credit (HELOCs), this measure can be thought of as a good proxy for the homeownership rate conditional on being in FD.

The rest of the table focuses on FD and shows that the model does well at reproducing the overall patterns. Indeed, the model very closely matches the fact that average delinquency rates rise with each quintile of FD, as do bankruptcy rates. In the model as in the data, the persistence of FD tends to fall over time within a given quintile and, perhaps counter-intuitively, also tends to fall across quintiles as FD increases.

Table 4 shows the resulting parameter estimates and reveals significant and systematic differences across quintiles of FD. Most notably, the share of impatient individuals rises from Q1 (least distressed) to Q5 (most distressed). In Q1, 30% of the population is impatient and discounts the future relatively more. In Q5, by contrast, nearly 60% of the population is impatient. Thus, between Q1 and Q5, there is nearly a doubling of this share. The model requires this divergence between Q1 and Q5 to match similarly significant differences between these quintiles in the data. First, the incidence of FD, measured by the DQ rate, is 2.7 times higher in Q5 than in Q1. Second, homeownership is nearly 15 percentage points lower in Q5 versus Q1. Lastly, net financial wealth to income is less than half as big in Q5 compared to Q1. A more significant share of impatient types in Q5 helps to generate these features.

Next, the model estimates imply significant heterogeneity in rental house sizes within and across quintiles. Focusing first on the within differences, recall that for all quintiles, the size of rental houses for patient \( H \)-types is close to zero, by assumption. The parameter estimates and standard errors in the middle of Table 4 therefore allow us to quickly reject the null of no differences in rental house size between \( L \)- and \( H \)-types, regardless of quintile of FD. Hence, rental house size heterogeneity is necessary for the model to match the data.

Turning to across quintile differences, the parameter estimates and standard errors also
<table>
<thead>
<tr>
<th>Table 3: Model Fit by Quintile of FD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>SAVINGS/INCOME</td>
</tr>
<tr>
<td>Savings/income</td>
</tr>
<tr>
<td>HOME OWNERSHIP</td>
</tr>
<tr>
<td>HOUSING LEVERAGE</td>
</tr>
<tr>
<td>WITH HOUSING DEBT</td>
</tr>
<tr>
<td>WITH HOUSING DEBT / IN FD</td>
</tr>
<tr>
<td>HOUSING DEBT/INCOME</td>
</tr>
<tr>
<td>MORTGAGE DEFAULT RATE</td>
</tr>
<tr>
<td>DQ RATE</td>
</tr>
<tr>
<td>BK RATE</td>
</tr>
<tr>
<td>PERSISTENCE OF FD 2 YRS</td>
</tr>
<tr>
<td>PERSISTENCE OF FD 4 YRS</td>
</tr>
<tr>
<td>PERSISTENCE OF FD 5 YRS</td>
</tr>
<tr>
<td>PERSISTENCE OF FD 6 YRS</td>
</tr>
<tr>
<td>PERSISTENCE OF FD 8 YRS</td>
</tr>
<tr>
<td>PERSISTENCE OF FD 10 YRS</td>
</tr>
<tr>
<td>SSE</td>
</tr>
</tbody>
</table>

Notes: * in percent. SSE is the sum of squared errors for each quintile. “Wealth/Income” represents mean net financial wealth divided by mean income, and “With housing debt / In FD” is the percent of the population with housing debt, conditional on being in FD.

allow us to reject the null of equal rental house sizes for $L$-type individuals who live in Q1 versus Q5. Interestingly, the model requires a smaller value of $h^R_L$ in Q5 versus Q1. This finding has to do with matching the joint distribution of FD and homeownership. Impatient types tend more often to be in FD, so they must account for a majority of Q5 agents to reproduce the high levels of FD found there in the data. The data also shows that the Q5 homeownership rate is relatively high. However, impatience makes modeled agents less likely to have enough savings to finance home purchases. This discrepancy is resolved in the model by making homeownership comparatively more attractive to $L$ types in Q5 relative to Q1.
Hence, the smaller value of $h_R^L$ in Q5 versus Q1.

Lastly, the model also requires significant dispersion across quintiles in the probability of DQ debt being discharged, $\eta$. While this probability is 45% in Q1, it is just under 25% in Q5. As previously noted, while $L$-types will tend more often to be in FD, not all $L$-types will be in FD. Thus, to incentivize the DQ option in Q1, a higher discharge probability is required. In contrast, since the share of $L$ types is much higher in Q5, the discharge probability is not as high. Beyond affecting the incidence of FD, the discharge probability also affects its persistence. In an extreme case where very few individuals are in FD (as in Q1), FD would otherwise be very concentrated and persistent within the model. While FD is quite persistent in the data, that persistence quickly declines at longer time horizons. A higher discharge probability helps generate this relatively steep decline within Q1. Again, in contrast, the persistence of FD falls less dramatically in Q5, so the model there requires a lower discharge probability.

Table 4: Parameter Estimates by Quintile of FD

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_L$</td>
<td>0.297</td>
<td>0.385</td>
<td>0.442</td>
<td>0.497</td>
<td>0.575</td>
</tr>
<tr>
<td></td>
<td>(0.081)</td>
<td>(0.057)</td>
<td>(0.054)</td>
<td>(0.046)</td>
<td>(0.042)</td>
</tr>
<tr>
<td>$h_R^L$</td>
<td>4.500</td>
<td>4.362</td>
<td>3.943</td>
<td>2.988</td>
<td>2.985</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.036)</td>
<td>(0.028)</td>
<td>(0.035)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.449</td>
<td>0.294</td>
<td>0.277</td>
<td>0.244</td>
<td>0.244</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
</tbody>
</table>

Notes: Asymptotic standard errors appear in parentheses.
4.2 Aggregate shock calibration

Having estimated five different economies to capture the wide dispersion of FD across the US, we now focus on replicating the correlation between FD and aggregate shocks observed in the GR and CV19 pandemic data. To do so, we create two stylized recessions that mimic how shocks were distributed across FD regions. The first is an unexpected permanent decline in house prices, similar to that observed during the GR. Since houses are assets and estimates of an autoregressive process for prices are very close to a random walk, we assume house price shocks are permanent. The second is an unexpected temporary decline in labor income, similar to the CV19 pandemic. Since most of the effect of the pandemic on labor earnings in the US was short-lived, we assume that these income shocks are temporary. In both cases, our quantitative analysis treats these shocks as exogenous and is not meant to capture all the features of these downturns. Instead, our goal is to understand how aggregate shocks transmit into consumption changes when FD is an option and when it is correlated with shock exposure.\textsuperscript{14}

Table 5 shows the shocks hitting each quintile of FD and reveals significantly different experiences across quintiles for each of the considered downturns. In terms of house-price shocks, we use the data presented in Section 2.2 to calculate the average change in house prices between 2007 and 2008 for each quintile.\textsuperscript{15} In terms of labor earnings shocks, we construct the distribution of earnings losses from the survey done by Bick and Blandin (2021).

Table 5: Calibration of House-price and Income Shocks

<table>
<thead>
<tr>
<th>FD Quintile</th>
<th>Average decline in house prices</th>
<th>Percent of population with earnings loss of:</th>
<th>Average earnings loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>7.0</td>
<td>80.3 5.3 14.4</td>
<td>8.5</td>
</tr>
<tr>
<td>2</td>
<td>8.6</td>
<td>79.3 5.6 15.1</td>
<td>9.0</td>
</tr>
<tr>
<td>3</td>
<td>10.0</td>
<td>78.2 5.1 16.7</td>
<td>9.6</td>
</tr>
<tr>
<td>4</td>
<td>10.9</td>
<td>76.5 5.9 17.6</td>
<td>10.3</td>
</tr>
<tr>
<td>5</td>
<td>11.5</td>
<td>72.4 5.9 21.7</td>
<td>12.3</td>
</tr>
</tbody>
</table>

Sources: Zillow and Bick and Blandin (2021).

These distributions highlight the positive relationship between aggregate shocks and FD. In terms of house prices declines, the Q1 economy (lowest FD) only experiences a 7% decline
\textsuperscript{14}For a rich analysis of the decline in house prices observed during the GFC see Garriga and Hedlund (2017).
\textsuperscript{15}We obtain very similar results using the average yearly change between 2006 and 2009 as well.
in house prices. Meanwhile, the Q5 economy (highest FD) experiences an 11.5% decline in house prices. For labor earnings declines, the disparity is even starker. Focusing on severe earnings losses (a 50% decline relative to pre-shock earnings), roughly 14% of households in Q1 receive this type of shock, compared to nearly 22% of households in Q5.

5 Model validation

Our main goal, having pinned down the correlation between FD and shock exposure, is to better understand how the joint distribution of FD and shocks affects consumption losses across quintiles and the aggregate economy. Before examining this in Section 6 however, it is important to ensure that the consumption responses generated by the model are realistic. We now verify the extent to which the degree of transmission of shocks (to either house prices or income) into consumption in each of the five economies is consistent with externally determined empirics. To do so, we present model-implied MPCs out of house-price and income shocks. The similarities with empirical estimates that we find are reassuring, providing empirical support to the quantitative claims we make in Section 6.

5.1 Transmission of housing shocks

First, we consider how consumption responds to the house-price shocks described in the previous section. It takes time for consumption in each quintile to adjust after a permanent shock. To capture the change over time, we calculate the average annual MPC over three years following the housing shock.\textsuperscript{16} The results are displayed in Table 6.

<table>
<thead>
<tr>
<th>Table 6: MPC Out of House-price Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate (lowest FD)</td>
</tr>
<tr>
<td>All Households</td>
</tr>
<tr>
<td>Homeowners</td>
</tr>
<tr>
<td>Homeowners, Uncorrelated Shocks</td>
</tr>
</tbody>
</table>

The first cell of this table shows an aggregate MPC is 7 cents per dollar. This number is within the range of estimates in Mian, Rao, and Sufi (2013), who report numbers between 0.054 to 0.119. In particular, their IV specification delivers an MPC of 0.072, which is very similar to our baseline number. Interestingly, the remainder of the first row shows only minor differences in the MPC out of housing shocks as FD rises.

\textsuperscript{16}Calculating MPCs for shorter or longer time horizons does not alter our conclusions.
If we focus our attention on the consumption responses of homeowners, as done in the second row, we obtain a larger aggregate MPC and more dispersion in MPCs across quintiles. Now, the aggregate MPC is nearly 8.7 cents per dollar. Additionally, we find MPCs increase with FD from a low of 8.1 cents per dollar (in Q1 and Q2) to a high of 9.5 cents per dollar (in Q5).

That homeowners mainly drive the aggregate change in consumption aligns with Aladangady (2017). Our model, however, ascribes a small and subtle effect to renters as well. In the model, renters who will eventually become homeowners experience a small positive income effect from lower house prices that allows them to consume more while still purchasing houses as planned. In contrast, established homeowners experience a negative wealth effect and thus decrease their consumption.

The last row of Table 6 highlights the role of nonlinearities in shaping the model implied MPCs. Focusing our attention again on homeowners, now subjecting all quintiles to the same house price decline delivers a slightly larger aggregate MPC of nearly 9 cents per dollar. Here too, we observe a large dispersion on MPCs across quintiles of FD ranging from roughly 8 cents per dollar (Q1) to nearly 10 cents per dollar (Q5). These findings are consistent with the estimated nonlinear effect that Mian, Rao, and Sufi (2013) report.\footnote{That is, MPCs being larger (smaller) for smaller (larger) house price shocks.}

5.2 Transmission of income shocks

To validate the modeled income shocks, we next consider the MPC out of the income shocks described in Section 4.2. We find an aggregate MPC of $0.308 per $1 transitory increase in income. This MPC is similar to that in Sahm, Shapiro, and Slemrod (2010), who report “an aggregate MPC after one year of about one-third.” The size of this response is also close to empirical estimates like those in Coronado, Lupton, and Sheiner (2005) and Jappelli and Pistaferr (2006).

<table>
<thead>
<tr>
<th>MPC Out of Income Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggregate Q1 Q2 Q3 Q4 Q5</td>
</tr>
<tr>
<td>(lowest FD) (highest FD)</td>
</tr>
<tr>
<td>MPC .308 .239 .287 .317 .331 .385</td>
</tr>
</tbody>
</table>

The results for individual quintiles show that there is significant heterogeneity behind this aggregate number, where higher FD is associated with a higher consumption sensitivity per dollar of income lost. In particular, the difference in MPCs between the least and most
distressed quintiles ($0.239$ vs. $0.385$) is in line with the empirical evidence presented in Parker (2017) that households with low liquidity spend at a significantly higher rate than that of high liquidity households. Parker (2017) further argues that “the majority of lack of consumption smoothing is predicted by a simple measure that can be interpreted as impatience.” This also supports our findings on FD.

In addition to this income shock meant to simulate the economic downturn surrounding COVID-19, modeled agents undergo shocks to their income process each period in the steady state. To validate the modeled response to these more routine income shocks, we calculate the consumption insurance coefficients, which give the portion of income shocks that do not transfer into consumption changes. Table 8 displays these coefficients calculated directly from realizations of individual shocks as in Kaplan and Violante (2010), and compares them against data-based estimates from Blundell, Pistaferri, and Preston (2008).

<table>
<thead>
<tr>
<th>Table 8: Consumption Insurance Coefficients for Income Shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>(lowest FD)</td>
</tr>
<tr>
<td>BPP (2008)</td>
</tr>
<tr>
<td>Transitory</td>
</tr>
<tr>
<td>Permanent</td>
</tr>
</tbody>
</table>

Our model’s consumption insurance coefficients are similar to Blundell, Pistaferri, and Preston (2008) for both permanent and transitory shocks. However, the model’s prediction is closest for permanent shocks, replicating 92% of the corresponding empirical estimate. In the case of transitory shocks, our aggregate coefficient is quantitatively closer to what Kaplan and Violante (2010) obtain with a zero borrowing constraint economy. This result suggests the modeling of FD plays a vital role in quantitatively restricting the degree to which agents can ensure their consumption against transitory income shocks.

Looking across quintiles of FD reveals a systematic relationship between FD and the degree of consumption insurance. The gap in insurance coefficients between Q1 and Q5 is 8 percentage points (or just under 10%) for transitory shocks and 5 percentage points (or roughly 14%) for permanent shocks. Overall, the heterogeneity in insurance coefficients

---

The coefficient is therefore very closely related to the MPC, but we include both measures here because they are calculated in different ways. Two of the more significant differences are that (i) the insurance coefficients are calculated over the full economy while the MPC is only calculated for working agents, and (ii) the income shock considered for the MPC is negative, while the shocks used for the insurance coefficients can be either positive or negative. This makes for a significant difference when agents are up against borrowing constraints. Thus, it would be incorrect to expect that the insurance coefficients will be equal to one minus the MPC, as might otherwise be assumed.
across quintiles of FD shows that areas with higher FD are less able to weather income shocks without altering their consumption.

6 Quantitative results

With our model in hand, we now quantitatively assess the importance of accounting for FD and its correlation with aggregate shocks. Following the empirical results from Section ??, we first discuss the results for house-price shocks and then income shocks. Because FD may carry both aggregate and individual consequences, we consider a broad spectrum of consumption-based measures following each of these two modeled shocks. Additionally, we examine how FD and its correlation matter through a series of channels for each of these measures. Overall, we find that FD matters in different ways depending on the type of aggregate shock considered. Interestingly, however, the correlation of FD with aggregate shocks does not seem to carry aggregate consequences for either type of shock.

To get a broad view of FD’s impact on consumption, we focus on three outcomes following a shock: (i) the response of aggregate consumption; (ii) the dispersion in consumption responses across households; and (iii) the change in consumption-based poverty. The first is a natural gauge of aggregate consequences of recessions, while the latter two outcomes highlight how FD and its correlation with aggregate shocks may exacerbate consumption inequality. Indeed, in their work “Macroeconomic performance and the disadvantaged,” Cutler and Katz [1991] argued that recessions in the 1970s-80s brought substantial increases in poverty. Here we find that considering FD is crucial to understand the effect of the last two recessions on the most disadvantaged.

For each of these outcomes, we decompose the importance of FD through three channels: (i) FD may matter directly since it allows for another margin of adjustment to insulate consumption from shocks; (ii) FD may also matter indirectly because its persistence, viewed through the lens of our model, implies a significant degree of ex-ante heterogeneity across agents; and lastly, (iii) FD may matter through its positive correlation with aggregate shocks. As noted in the introduction, we refer to these as the direct, indirect and correlation channels of FD.

Isolating these channels is done through a series of counterfactual economies. Each counterfactual economy is a special case of our baseline economy. Importantly, each one places increasingly more simplifying restrictions on our baseline model:

(1) Baseline model with uncorrelated shocks: We compute the size of the shock to house prices and income such that the aggregate decline in house prices and income is the
same in our stylized versions of the GR and CV19 recessions. Then, we hit each of the five “regions” with that common shock.

(2) No debt, ex-ante heterogeneous agents model with uncorrelated shocks: We remove FD from the previous model by disallowing unsecured borrowing altogether. In practical terms, we impose a zero borrowing constraint.\footnote{We also did this exercise in an alternative model having unsecured debt but disallowing default. The predictions regarding the response of consumption to shocks are similar to the model with no borrowing presented here.} Although there is no FD (and no correlation with shocks), we still assume there are five different “regions” that differ in preferences as in (1).

(3) No debt, ex-ante identical agents model with uncorrelated shocks: We use the model described in (2), but we assume agents are ex-ante identical, as is common in the literature. In other words, this is a single “region” model, recalibrated to match some standard targets.\footnote{See Appendix D}

By comparing our baseline model with (1), we obtain an estimate of correlation channel of FD. Isolating the relative strengths of the direct and indirect channels of FD requires comparing (1), (2), and (3). A comparison between (2) and (3) helps isolate the indirect channel of FD. With this information, an estimate of the direct channel can be recovered from the comparison of (1) and (2).

Because we are interested in how FD affects three outcomes via its three channels, all for two distinct shocks, we provide a simple graphical summary of our key results below. The top panel of Table 9 collects our main results about house-price while the bottom panel presents the results for income shocks. In each panel, the rows represent the outcomes we consider, while the columns represent each of the channels of FD. The checkmark symbol in each cell means that a particular channel matters for a given outcome.

Table 9 shows that even though the two shocks we analyze are very different, they share many similarities viewed through the lens of FD. Across both shocks, the correlation of FD with aggregate shocks is unimportant for aggregate outcomes. Similarly, across both shocks, the indirect channel of FD affects all outcomes considered. Lastly, across both shocks, the direct channel of FD has aggregate and cross-sectional consequences.

Below we provide the quantitative details underlying this table as some effects are stronger than others or of the opposite sign. First, we describe the results for house-price shocks and then present the equivalent results for income shocks. In each case, we first go over aggregate consequences, followed by cross-sectional outcomes, and finalize with the implications for consumption-based poverty.
Table 9: Summarizing Key Results

<table>
<thead>
<tr>
<th>Outcome</th>
<th>Channel of FD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direct</td>
</tr>
<tr>
<td><strong>House-price shocks</strong></td>
<td></td>
</tr>
<tr>
<td>Aggregate</td>
<td>✓</td>
</tr>
<tr>
<td>Cross-sectional</td>
<td>✓</td>
</tr>
<tr>
<td>Poverty</td>
<td>✓</td>
</tr>
<tr>
<td><strong>Income Shocks</strong></td>
<td></td>
</tr>
<tr>
<td>Aggregate</td>
<td>✓</td>
</tr>
<tr>
<td>Cross-sectional</td>
<td>✓</td>
</tr>
<tr>
<td>Poverty</td>
<td>✓</td>
</tr>
</tbody>
</table>

6.1 House-price shocks

Focusing on house-price shocks, we find that FD matters directly and indirectly for all three of the outcomes we measure. The signs and magnitudes of these effects vary depending on the outcome being measured and whether we focus on homeowners or examine all individuals. Very consistently, however, we find the correlation channel does not matter for aggregate outcomes.

6.1.1 Aggregate consequences

The top panel of Table 10 shows that the correlation channel of FD is relatively unimportant in comparison to the direct and indirect channels in shaping the response of aggregate consumption to house-price shocks. The first column of this table collects the aggregate response of the baseline model, while the remaining columns display the corresponding responses of each of the counterfactual economies previously described.

To see the unimportance of the correlation channel, consider columns (1) and (2), where the only difference between columns is the correlation of shocks. As can be seen, the responses are very similar at -1.78% and -1.83%, respectively. Looking specifically at homeowners alone, we see very similar responses across the two columns at -2.87% and -2.93%.

As shown in the following subsection, part of the reason the aggregate changes are so similar is how low FD areas balance out high FD areas. When shocks are uncorrelated, the smaller consumption response among high FD areas (who now receive smaller shocks) is counterbalanced by the larger consumption response among low FD areas (who now receive larger shocks). Importantly, since low FD areas account for a larger share of aggregate consumption, their smaller response more than offsets the more severe response of high FD regions.
<table>
<thead>
<tr>
<th></th>
<th>Baseline model cor. shocks</th>
<th>Baseline model uncorr. shocks</th>
<th>No debt, ex-ante het. agents model uncorr. shocks</th>
<th>No debt, ex-ante id. agents model uncorr. shocks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>House-price shocks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All households</td>
<td>-1.78</td>
<td>-1.83</td>
<td>-1.22</td>
<td>-1.08</td>
</tr>
<tr>
<td>Homeowners</td>
<td>-2.87</td>
<td>-2.93</td>
<td>-2.03</td>
<td>-2.11</td>
</tr>
<tr>
<td><strong>Income shocks</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All households</td>
<td>-3.35</td>
<td>-3.26</td>
<td>-2.99</td>
<td>-1.47</td>
</tr>
</tbody>
</table>

Notes: All values are measured as percentage changes relative to the old steady-state. In the housing shock case, these are average changes over three periods following the shock. In the income shock case, the change is measured only in the period of the shock and is calculated over the working-age population since retired agents do not lose any income.

Disentangling the importance of the other two channels requires analyzing columns (2), (3), and (4). Column (3) of the table considers the model with no debt, ex-ante heterogeneous agents, and uncorrelated shocks with FD. Meanwhile, column (4) considers the model with no debt, ex-ante identical agents, and shocks that are also uncorrelated with FD. Comparing columns (2) and (4) shows that if both direct and indirect channels are removed, the drop in aggregate consumption is reduced from -1.83 to -1.08% (0.75ppt). In other words, these two channels tend to amplify the response of aggregate consumption to house-price shocks.

Adding back the indirect channel, as done in column (3), brings the drop in aggregate consumption to -1.22%, still 0.61ppt off column (2). This finding suggests that about 80% of the drop in aggregate consumption is due to the direct channel, while the remaining 20% is due to the indirect channel.

Looking specifically at homeowners suggests both direct and indirect channels matter, but in opposite directions. Comparing columns (2) and (4) shows that if direct and indirect channels are removed, the drop in consumption among homeowners is reduced from -2.93 to -2.11% (0.82ppt). Hence, these two channels tend to amplify the drop in consumption of homeowners following a house-price shock on the net. This number, however, masks opposing forces between the indirect and direct channels of FD. Adding back the indirect channel, as done in column (3), brings the drop in consumption to -2.03% (i.e. the drop in consumption is lessened). Thus, the indirect channel increases consumption of homeowners by 0.08ppt, while the direct channel decreases it by 0.9ppt delivering a net decrease of 0.82ppt.

Part of the reason why the indirect channel of FD lessens the drop in consumption among homeowners has to do with the correlation between financial wealth and homeownership that
the ex-ante preference heterogeneity introduces. In models with this heterogeneity, financially poor individuals are less likely to own a house than in the simpler model without ex-ante heterogeneity. This finding is because the estimated ex-ante heterogeneity implies that low-$\beta$ individuals are also individuals who derive comparatively more utility from renting compared to high-$\beta$ individuals who favor homeownership. As a result, the pool of homeowners in the model with ex-ante heterogeneity is less financially fragile, making them more able to weather house-price declines. In contrast, once this ex-ante heterogeneity is removed, the pool of homeowners now includes more financially fragile individuals (as all individuals value homeownership equally), making the pool less able to weather house-price declines. Overall, this composition effect induced by the correlation between financial wealth and homeownership is modest and leads to a minor positive effect of the indirect channel of FD on consumption.

The reason why the direct channel of FD worsens the drop in consumption among homeowners has to do with differences in financial positions and debt pricing between the models with and without FD. Given a zero borrowing constraint in the no-debt model, most homeowners have at least some financial savings that they can use to smooth consumption in a house-price decline. With the endogenous borrowing constraints generated in the economy with FD, some homeowners are financially indebted to begin with and thus are less able to smooth consumption. Furthermore, since the price of financial debt responds to house prices and the home equity position of borrowers, some households see their debt constraints tighten when house prices decline, which exacerbates their inability to smooth consumption. Overall, these effects are much more significant than the aforementioned indirect effects of FD. As a result, the net effect of FD on aggregate consumption is to amplify the reduction in spending following a house-price decline.

6.1.2 Cross-sectional consequences

Figure 7 illustrates how all three channels of FD influence cross-sectional differences in the response of consumption to house-price shocks. It presents the average consumption response to a permanent house-price decline among homeowners by quintile/region of FD and for each of the previously described models. The solid purple line with circles represents the baseline model when shocks are correlated with FD. The solid lavender line with squares represents the baseline model when shocks are uncorrelated with FD. Finally, the solid blue line with triangles represents the no debt, ex-ante heterogeneous agents model when shocks are uncorrelated with FD. Recall, in the case of the baseline model with correlated shocks, these shocks are distributed by FD according to the second column of Table 5. In all other cases, each quintile is subject to an identical shock that generates the same aggregate decline.
in house prices as the baseline scenario.

Consistent with the motivating findings in Figure 2 of the introduction, the slope of the purple line with circles suggests that the baseline model generates a significant relationship between FD and the transmission of house-price shocks to consumption. A 2.3ppt gap emerges between the consumption responses of the quintile with the most ex-ante FD (Q5) and the one with the least (Q1).²¹

Comparing the purple line with circles and the lavender line with squares suggests that the positive correlation of FD with house-price shocks tends to amplify the gap in consumption responses across areas differing in FD. The flatter slope of the lavender line delivers a smaller gap between the response of Q5 and Q1 of only 0.92%. Thus, about 60% of the Q5-Q1 gap from the baseline model with correlated shocks is the consequence of the positive correlation between FD and house-price declines. The remaining 40% is the result of FD alone through its direct and indirect channels.

The remaining lines reveal that most of the remaining Q5-Q1 gap is related to the indirect channel of FD, while a smaller portion is related to the direct channel of FD. Note that the ex-ante heterogeneous agent model with uncorrelated shocks and no FD—blue line with triangles—captures the same pattern in consumption responses as the baseline model with uncorrelated shocks—lavender line with squares. Importantly, though, this model generates a slightly larger Q5-Q1 gap of about -1.10ppt. That any gap exists at all is a consequence of the indirect channel because FD has no direct role by construction. However, the fact that the gap is more significant than the one predicted by the comparable model with FD suggests the direct channel of FD tends to attenuate cross-sectional differences in the response of consumption to house-price shocks.

That the direct channel of FD plays differing roles in the cross-section versus aggregate highlights the importance of analyzing FD through several measures. Recall from the previous subsection, the direct channel of FD amplifies the average drop in consumption among homeowners. Meanwhile, the current results suggest this channel attenuates differences in consumption response across the FD distribution. This latter observation highlights how FD as a form of debt repudiation provides some consumption insurance, which helps shrink (albeit modestly) the gap in consumption responses between the most and least financially vulnerable regions.

²¹The consumption response is also increasing in FD when we include all households. However, the associated Q5-Q1 gap is smaller at 0.66 percentage points because homeownership is more prominent in regions with less FD. This difference between the gaps is that non-homeowners often experience the house price decline as a positive wealth shock. Thus, even though homeowners in greater FD react more strongly than homeowners in less FD, this effect is dampened because these quintiles also tend to have a more significant percentage of non-homeowners.
Figure 7: Consumption Responses to House-price Shocks by Quintile of FD and Model

Notes: All values are measured as percentage changes relative to the old steady state. These are average changes over three periods following the shock and include only homeowners. The solid purple line with circles represents the baseline model when shocks are correlated with FD. The solid lavender line with squares represents the baseline model when shocks are uncorrelated with FD. The solid blue line with triangles represents the no debt, ex-ante heterogeneous agents model when shocks are uncorrelated with FD.

6.1.3 Implications for consumption-based poverty

Motivated by the findings in Cutler and Katz (1991), we analyze how FD through its three channels shapes the response of consumption-based poverty to house-price shocks. We follow Meyer and Sullivan (2019) and target a consumption-based poverty threshold of 13% in a steady-state, matching the average poverty rate for 2015-2018. Then, we measure how the population share below this threshold changes in response to house price shocks.

Table 11 shows that consumption-based poverty actually tends to decline in our model following a house-price decline. Column (1) shows that poverty declined by 0.28 percentage points after declining house prices in the baseline economy with correlated shocks. While somewhat counter-intuitive, this reflects the fact that lower house prices increase affordability, which helps consumption-poor and low wealth households. The remaining columns of the top row show how all three channels of FD shape this decline in poverty.

Column (2) shows that the correlation channel of FD tends to increase poverty following
house-price declines. As this column shows, the drop in poverty is larger when shocks are uncorrelated, falling from -0.28 to -0.35ppt, or a 25% difference. This result is because affordability rises even more in low FD regions with uncorrelated shocks since they are now subject to larger house-price declines. The greater affordability increase in areas where ownership is more financially feasible helps reduce consumption-based poverty even more. In contrast, with correlated shocks, greater affordability is bestowed to areas that are less able to take advantage of it; hence, poverty falls by less. While the correlation channel’s impact on poverty is noteworthy, the direct and indirect channels of FD play even larger roles in generating changes in consumption-based poverty.

Focusing first on the no debt economy of column (3) suggests the direct channel of FD also tends to increase poverty following a house-price decline. As this column shows, the drop in poverty is more considerable when FD is removed, falling from -0.35 to -0.56ppt, or a 60% difference. In this model, poorer agents are in a better financial position and can take additional advantage of the aforementioned affordability effect. Consequently, the poverty reduction is even more significant compared to the baseline economy with uncorrelated shocks.

This finding highlights the importance of modeling FD when analyzing how house-price shocks affect the most disadvantaged. When house prices decline, consumption-based poverty falls in the baseline model (regardless of the correlation of shocks) because affordability rises. This effect, however, is moderated by the fact that the most disadvantaged are also in FD and cannot readily purchase houses given their weaker financial position. Once FD is removed, as in the no debt economy, the most disadvantaged are no longer in FD (by construction) and can take advantage of the increased affordability. This finding suggests that consumption-saving models which omit the FD choice may overstate the poverty-reducing effects of house-price declines on the most disadvantaged.

Column (4) of this table suggests the indirect channel of FD tends to decrease poverty following a house-price decline. As can be seen in this column, removing the indirect channel allows poverty to rise rather than fall. The difference between columns (3) and (4) is significant, flipping from -0.56 to +0.47ppt, or nearly a percentage point. This result is due to the relationship between poverty and homeownership implied by the ex-ante heterogeneity encoded in the data on FD. As noted in the previous subsection, in the no-FD economy with identical agents, financially poor individuals are counterfactually more likely to own a house and more likely to suffer from the reduction in house prices compared to the same economy with ex-ante heterogeneity. With ex-ante heterogeneity, financially poor individuals are less likely to own homes and thus less likely to suffer from house price declines. This finding suggests that consumption-saving models that omit the heterogeneity that FD encodes may
miss the poverty-reducing effects of house-price declines on the most disadvantaged unless they adequately replicate the relationship between financial fragility and homeownership found in the data.

Overall, FD matters through all three channels in shaping the response of consumption-based poverty to house-price shocks. FD matters directly because individuals in FD are naturally financially constrained and thus less likely to benefit from the increase in housing affordability brought by a reduction in house prices. In other words, the direct channel of FD tends to increase consumption-based poverty in response to house-price shocks. FD also matters indirectly because the ex-ante heterogeneity it encodes implies financially fragile individuals are also less likely to own homes. In other words, the indirect channel of FD tends to decrease consumption-based poverty by getting the relationship between financial fragility and homeownership right. Lastly, the correlation channel of FD effectively increases poverty as it implies that affordability rises in areas less able to benefit from it.

<table>
<thead>
<tr>
<th>Table 11: Change in Consumption-based Poverty By Model and Shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline model corr. shocks</td>
</tr>
<tr>
<td>(1) House-price shocks</td>
</tr>
<tr>
<td>(2) Income shocks</td>
</tr>
</tbody>
</table>

Notes: All values are measured as percentage point changes relative to the model-specific steady state population in poverty of 13%. In the housing shock case, these are average changes over three periods following the shock. In the income shock case, the change is measured only in the period of the shock.

6.2 Income shocks

Turning to income shocks like those experienced during the CV19 pandemic, we find that FD matters indirectly for all three of the outcomes we measure. Meanwhile, the other two channels are a bit more narrow on their impacts. In particular, much like was the case with house-price shocks, the correlation channel of FD amplifies the dispersion in consumption responses across households but does not affect aggregate outcomes.

6.2.1 Aggregate consequences

Focusing first on aggregate consequences, the bottom panel of Table 10 shows that FD’s correlation with aggregate income shocks is relatively unimportant. This point is readily
seen by comparing columns (1) and (2). These columns reveal that the aggregate decline in consumption only changes by 0.09ppt (or less than 3%) when shocks are correlated (-3.35%) or uncorrelated (-3.26%) with FD.

Rather, comparing remaining columns shows that FD affects these results both directly and indirectly. Removing FD altogether as done in column (4) reduces the drop in aggregate consumption from -3.26% to -1.47%. In other words, FD amplifies the drop in aggregate consumption by 1.79 ppt (or roughly 120%) through its direct and indirect channels. Allowing FD to enter indirectly shrinks this gap to 0.27ppt, as seen in column (3). Thus, of the 1.79ppt gap, 85% of it is due to the indirect channel of FD, while the remaining 15% is due to the direct channel.

Compared to the case with house-price shocks, the relative importance of the direct versus indirect channels in aggregate is reversed when the economy is subject to income shocks. In the case of house-price shocks, the direct channel of FD accounted for roughly 80% of the amplification shocks. In contrast, in the case of income shocks, the direct channel only accounts for 15% of the amplification of shocks. This finding highlights an important difference between house-price shocks and income shocks when viewed through the lens of FD. Since house-price shocks affect an asset held by households, the direct channel of FD is more important than the indirect channel as the former places a rich asset/debt structure on the economy. In contrast, when faced with transitory income shocks the indirect channel of FD is more important. That the asset/debt structure plays a less important role in shaping the response of consumption to transitory income shocks is reminiscent of the results in Kaplan and Violante (2010). They find a similar amount (and close to the data) of consumption insurance against transitory income shocks in models with no borrowing or natural borrowing constraints.

### 6.2.2 Cross-sectional consequences

Turning to the response of consumption to a transitory change in income, Figure 8 illustrates that, much like with house-price shocks, all channels of FD are important for understanding cross-sectional differences in the response of consumption to income shocks. Focusing first on the baseline model with correlated shocks, note that the solid purple line with dots in this figure delivers a large Q5-Q1 gap of -2.95ppt.\(^{22}\) While this response appears large relative to what has been seen thus far during the CV19 pandemic, it is essential to note that our model abstracts from any monetary or fiscal policy interventions. Instead, our model suggests that absent any policy interventions, households would be expected to respond sharply and

---

\(^{22}\)In this experiment, the consumption change is measured in the period of the shock and only calculated over the working-age population since retired agents do not lose any income.
unevenly to an unforeseen income shock like that experienced during the pandemic.

Comparing the baseline model with correlated shocks to the baseline model with uncorrelated shocks shows how the uneven response across quintiles of FD is exacerbated by the correlation channel. Most notable is the big difference in the prediction for Q5 across models. The lavender line with squares represents the baseline model with uncorrelated shocks and implies a smaller Q5-Q1 gap than the baseline model with correlated shocks. Specifically, the gap declines from -2.95 to -1.51ppt, implying that nearly half of the Q5-Q1 gap from the baseline model is due to the correlation channel of FD.

When combined with the results on house-price shocks, this suggests the correlation channel was active across the FD distribution during the past two downturns. Recall, in the case of house-price shocks, roughly 60% of the corresponding Q5-Q1 gap was due to the correlation channel of FD. Thus, while the correlation channel appears to have been unimportant at the aggregate level over the past two recessions, this masks essential differences between the most and least financially fragile regions that can be attributed to this channel.

Next, comparing the baseline model with uncorrelated shocks to the no-debt model with ex-ante heterogeneity shows very clearly that the remaining half of the headline Q5-Q1 gap is mainly due to the indirect channel of FD. The no-debt model with ex-ante heterogeneity and uncorrelated shocks (solid blue line with triangles) mirrors the baseline model with uncorrelated shocks. This finding suggests that modeling FD directly is not very important in generating cross-sectional differences in consumption response to income shocks. The Q5-Q1 gap of the no-debt model with ex-ante heterogeneity and uncorrelated shocks is roughly 80% of the gap implied by the baseline model with uncorrelated shocks. The remaining 20% can be ascribed to the direct channel of FD.

When combined with the results on house-price shocks, this suggests that once the correlation channel is netted out, the indirect channel of FD is the dominant channel across the FD cross-sectional distribution regardless of shock type. In the case of house-price shocks, conditional on homeownership, the indirect channel of FD accounts for all of the Q5-Q1 gap that remains after accounting for the correlation of shocks as the direct channel goes in the opposite direction. Here the majority of the Q5-Q1 gap in response to income shocks is also accounted for by the indirect channel of FD.

### 6.2.3 Implications for consumption-based poverty

Finally, we can see that FD shapes the response of consumption-based poverty to income shocks through its indirect channel, while the other two channels are less relevant. First, note that consumption-based poverty increases in our baseline model with correlated shocks. The first cell in the bottom row of Table 11 shows that consumption-based poverty rises by 2.2ppt
Figure 8: Consumption Responses to Income Shocks by Quintile of FD and Model

Notes: All values are measured as percentage changes relative to the old steady state. In the housing shock case, these are average changes over three periods following the shock and include only homeowners. In the income shock case, the change is measured only in the period of the shock and includes only workers. Solid lines represent the aggregate change across all quintiles.

(or roughly 17%) relative to the steady-state level of 13%. While this once again appears counterfactual relative to the recent CV19 experience, recall our framework abstracts from key automatic stabilizers like unemployment insurance, food stamps, etc., all of which may have contributed to the stabilization of consumption during the pandemic.\footnote{Indeed, the official income-based poverty rate in 2020 rose by 1ppt to 11.4% (the first increase in poverty after five consecutive annual declines) according to the 2020 and 2021 Current Population Annual Social and Economic Supplements (CPS-ASEC). This result suggests that government transfers played a crucial role in shielding consumption from the increase in poverty.}

Similar to the case with house-price shocks, the correlation of FD with aggregate income shocks appears to be comparatively unimportant in generating this increase in consumption-based poverty. Column (2) shows an increase of 2.13ppt in consumption-based poverty in the baseline model with uncorrelated shocks. As this increase is 96% of the headline figure, it suggests that the \textit{correlation} channel of FD is relatively unimportant for shaping the response of poverty to income shocks.
Instead, the *indirect* channel of FD is critical for understanding the transmission of income shocks to poverty. Column (3) of the bottom row shows that removing FD as a form of debt repudiation still yields a similar increase in poverty at 2.14ppt. On the contrary, removing debt repudiation and the ex-ante heterogeneity that FD encodes (column 4) implies an increase in poverty of only 1.08%, or roughly 50% smaller. Overall, the *indirect* channel of FD is critical for generating the increase in poverty the baseline model implies.

Thus, in terms of poverty, the *indirect* channel of FD has opposite effects depending on the type of shock afflicting the economy. In the case of house-price shocks, the *indirect* channel of FD is associated with reductions in poverty. This is because the ex-ante heterogeneity that FD encodes implies that less patient and more financially vulnerable individuals are less likely to own houses and thus are less likely to suffer from reductions in home value (i.e. the most vulnerable are less likely to be affected). In contrast, in the case of income shocks, the *indirect* channel of FD is associated with increases in poverty. This finding is because the ex-ante heterogeneity that FD encodes implies that individuals are more impatient and financially vulnerable than in the model with no ex-ante heterogeneity. As a result, the likelihood of entering into poverty is higher in the model with ex-ante heterogeneity (i.e. because more vulnerable individuals exist).

7 Concluding remarks

Our paper aims to understand how household financial distress (FD) and its correlation with aggregate shocks shape individual and aggregate dynamics over the last two recessions. We first documented that FD and exposure to aggregate shocks in the Great Recession and the ongoing COVID-19 pandemic were positively correlated. We then developed a rich model of consumer debt, portfolio choice (including, critically, housing and mortgage-debt choice), and debt repayment to assess the importance of FD and its correlation with aggregate shocks in transmitting shocks to individual and aggregate consumption.

Taken as a whole, our findings suggest that the documented positive correlation of FD and shock exposure amplifies cross-sectional differences in the response of consumption to shocks (and hence inequality), even though such effects would not be seen if one only focused on aggregate consequences—which turn out to be relatively small. Even though the most financially vulnerable are the hardest hit during downturns, their share of aggregate consumption is comparatively small. By contrast, even modest movements in the consumption of the least distressed have larger aggregate consequences.

Beyond its correlation with aggregate shocks, our model’s counterfactuals suggest an essential role of FD, both as a modeled choice and because of the heterogeneity it encodes,
in understanding how shocks propagate to consumption. For questions regarding shocks to asset prices, like house values, our results suggest the specific modeling of FD matters. However, for other shocks, like income shocks, the debt market arrangement matters less. In these cases, the informational content of the data on FD, through the degree of ex-ante heterogeneity it reflects, is much more critical. This finding suggests our structural estimates and identification via panel data on FD may have broader use as they reflect fundamental differences across agents.

In terms of future research, our model is very well suited for assessing the impacts of emergency policies enacted during the COVID-19 pandemic, like debt forbearance. Additionally, our model can be used to understand survey results like those in Coibion, Gorodnichenko, and Weber (2020) that find that most households used stimulus checks to pay down debt and improve their financial positions. We intend to address these exciting questions in future work.

References

Aguiar, M., Bils, M., and Boar, C. Who are the hand-to-mouth?, October 2020.


Appendix

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A Empirical analysis

In the following subsections, we present detailed information about each variable and how it was constructed, as well as various empirical results to supplement those shown in the paper. Table A1 shows some initial summary statistics for the entire data set. The next subsections explain how the data set was constructed.

Table A1: Descriptive Statistics Across Zip codes

<table>
<thead>
<tr>
<th></th>
<th>Count</th>
<th>Mean</th>
<th>S.D.</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
</tr>
</thead>
<tbody>
<tr>
<td>Housing Net Worth Shock, 2006-9</td>
<td>14230</td>
<td>-0.098</td>
<td>1.035</td>
<td>-0.109</td>
<td>-0.030</td>
<td>0.005</td>
</tr>
<tr>
<td>Change in home value $000, 2006-9</td>
<td>14230</td>
<td>-38.905</td>
<td>64.130</td>
<td>-62.833</td>
<td>-13.200</td>
<td>2.300</td>
</tr>
<tr>
<td>Net Worth per Household $000, 2006</td>
<td>14230</td>
<td>487.854</td>
<td>934.963</td>
<td>159.956</td>
<td>269.338</td>
<td>496.700</td>
</tr>
<tr>
<td>Income Per Households, $000, 2006</td>
<td>14230</td>
<td>72.861</td>
<td>53.508</td>
<td>45.125</td>
<td>58.838</td>
<td>82.823</td>
</tr>
<tr>
<td>No. Hou. per zip code (ths), 2006</td>
<td>14230</td>
<td>11.390</td>
<td>6.399</td>
<td>6.703</td>
<td>10.968</td>
<td>15.305</td>
</tr>
<tr>
<td>Housing Leverage Ratio, 2006</td>
<td>14230</td>
<td>0.453</td>
<td>0.173</td>
<td>0.347</td>
<td>0.433</td>
<td>0.536</td>
</tr>
<tr>
<td>$\Delta_{06-09}$ auto spending per hou. $000</td>
<td>14230</td>
<td>-2.108</td>
<td>6.447</td>
<td>-2.525</td>
<td>-1.517</td>
<td>-0.835</td>
</tr>
<tr>
<td>Fraction in DQ30, 2006</td>
<td>14230</td>
<td>0.142</td>
<td>0.048</td>
<td>0.108</td>
<td>0.138</td>
<td>0.172</td>
</tr>
<tr>
<td>Fraction in CL80, 2006</td>
<td>14230</td>
<td>0.228</td>
<td>0.054</td>
<td>0.192</td>
<td>0.228</td>
<td>0.264</td>
</tr>
</tbody>
</table>

Notes: All statistics are weighted by the number of households in the first quarter of 2006 for each zip code. p25, p50, and p75 respectively give the 25th, 50th, and 75th percentiles.

Sources: IRS SOI, FRBNY Consumer Credit Panel/Equifax, Census Bureau, Zillow, SCF.

A.1 A geographically representative sample

Building a geographically representative sample from the FRBNY CCP/Equifax dataset over all the years considered in this study presents a slight challenge: small random samples 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 over the full country could fix this issue, but the resulting datasets become difficult to process. Instead, then, we divide the zip codes for which we have IRS Summary of Income (SOI) data into 10 groups by population size\footnote{24Specifically by using the “number of returns” field provided by the IRS SOI.} and oversample areas with lower population.

Specifically, we pull a 100 percent sample of individual Equifax records from the smallest zip codes by population and decrease that percentage linearly until pulling a 50 percent sample of Equifax records for the largest zip codes\footnote{25Zip-code level data on CL80 and DQ30 are available at this\footnote{26}link for the years 2006 and 2018.} In order to remain in our sample for a given quarter, individuals must be between 25 and 65 years old, inclusive\footnote{26Age is calculated using an individual’s recorded birth year, and so any records not including a birth year are also excluded.}. Then, we correct
for oversampling by reweighting using population data from the 2000 and 2010 Census.

A.2 Constructing measures of wealth and consumption

The household wealth portion of our dataset was constructed at the zip code and county levels using a method almost identical to that of Mian, Rao, and Sufi (2013). Net wealth is defined as the sum of housing wealth $H$ and financial wealth $FW$ less debt $D$. $H$ is calculated separately for zip codes and counties 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. The housing leverage ratio is then defined as the total housing debt in a geography divided by $H$. Total housing debt is the mean housing debt recorded in Equifax for each geography multiplied by the number of households in that geography, taken from the Census.

To construct $FW$, we began by using IRS 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 financial wealth recorded in the Survey of Consumer Finances (SCF) corresponding to that fraction. $FW$ at the county level is simply calculated as the sum of $FW$ in its component zip codes. $D$ 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. Next, we assign each geography a portion of the total debt from the SCF equal to that fraction.

In the regression analysis, we also use a measurement of consumption used in the literature, the new of new cars registrations. In particular, 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 zip-code and county. As noted by Mian, Rao, and Sufi (2013), these data are advantageous

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27To 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. Mian, Rao, and Sufi (2013) 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.

28Here we include mortgages, the home equity installment balance, and the home equity revolving balance.

29Mian, Rao, and Sufi (2013) used the Federal Flow of Funds for this purpose, but we use the Survey of Consumer Finances because it allows us to limit our financial wealth totals to those of a certain age range. Specifically, our model is calibrated to match dynamics among people who are 25 to 55 years old, and so we likewise restrict the data to that age range when setting calibration targets. As shown in Kuhn and Rios-Rull (2016), the SCF and Federal Flow of Funds match up quite nicely in terms of aggregates. The SCF is not available in every year, and so wherever necessary we interpolate linearly between available years.

30To 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.

31Because 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 in the Census.
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 Mian, Rao, and Sufi (2013) in allocating an annual share of the national Census Retail Trade amounts for “Auto, Other Motor Vehicle” to each zip code and county equal to the share of new autos that residents of each geography purchased in the Polk data. Recall that the main interest of our regression analysis is to evaluate if the MPC in these regressions varies with the level of FD in the zip-code, which motivates our link between FD and vulnerability.

A.3 Financial distress

As defined in Section ??, DQ30 gives the percentage of primary 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 percent of their credit limit during some quarter of the year.

A.3.1 The persistence of “pre-existing” regional FD

FD defined in this way is highly persistent over time at an individual level, as shown in Athreya, Mustre-del Río, and Sánchez (2019). Thinking of a zip code as a collection of individuals, it follows that there should be some slight persistence in FD characteristics at a community level as well, limited by the way that individuals sometimes move. In fact, however, FD at the zip-code level is much more persistent than would be expected if individual-level persistence were the only factor at play.

Given from the 2007 ACS data that the average person will move about 12 times in their lifetime, and assuming that those moves are distributed randomly over 80 years, a back of the envelope calculation suggests that this average person would move 2.6 times in the years 2001-2017. If there were no tendency for people to sort themselves into zip codes with similar FD patterns or be somehow influenced into FD by their surrounding community, we would therefore expect that a zip code’s FD in 2000 would carry little predictive power for its status in 2017. Conditional on a zip code having been in the worst quintile of FD in 2000, however, there is a 55 percent chance that it was still in the worst quintile 18 years later. This is over twice as likely as random chance would predict. In addition, zip codes that did leave the worst quintile did not move far: 24 percent had moved to quintile 4 by 2018, and only 4 percent had moved to the least-distressed quintile.

The persistence of regional FD helps us to disentangle the underlying pre-existing conditions of FD at the onset of an economic shock from an FD response endogenously made
due to the shock. For each shock we consider, distinguishing zip codes that temporarily entered FD in this way from those that were already in FD requires measuring FD somehow separately from this endogenous response. Because FD is so persistent, this can be done by measuring it for each zip code before the shock occurred. We specifically use FD measurements taken in 2002 for the housing shock modelling the Great Recession and measurements taken in 2018 for the income shock modelling the COVID-19 pandemic.

### A.3.2 Robustness of correlation between FD and the house-price Shock

First, we show that the correlation we established in Figure ?? in the main text holds if we replace home values by housing wealth as in Mian, Rao, and Sufi (2013). Figure A1 documents the main result: The incidence of the housing wealth shock upon zip codes was highly positively correlated with household FD, so that zip codes with higher FD in 2002 tended to experience heavier losses in the Great Recession.

**Figure A1:** Housing Wealth Shocks (2006-09) and FD (DQ30) in 2002

![Housing Wealth Shocks (2006-09) and FD (DQ30) in 2002](image.png)

Sources: IRS SOI, Zillow, FRBNY Consumer Credit Panel/Equifax, Census Bureau, SCF. Each dot represents the mean of that bin weighted by 2006 net wealth of bins with respect to DQ30.

Then, we show this correlation is robust to alternative definitions of FD, as can be seen in Figure A2. 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.

As would be expected from the regional persistence of FD discussed in appendix Section A.3.1 these results are also not dependent upon measuring FD in a particular year. Figure A3 shows that the same relationship holds when measuring FD just before the recession.
Figure A2: Robustness to the Definition of FD

Notes: “120 day Delinquency sometime 2000-06” gives 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, 2002” gives the percentage of people in a zip code both in FD under the CL80 definition and having debt indicative of owning a house (i.e., a mortgage or home equity line of credit). “DQ30 and Housing Debt, 2002” is similar.
Sources: IRS SOI, Zillow, FRBNY Consumer Credit Panel/Equifax, Census Bureau, SCF. Each dot represents the mean of that bin of FD weighted by 2006 net wealth.

A.4 Regressions

There is an increasing relationship between FD and a zip code’s marginal propensity to consume, as illustrated in Figure 2. The more prevalent FD within a zip code, the more its residents tended to cut consumption of autos in response to a dollar decline in their housing wealth during the Great Recession. This section presents the regression results used to construct that figure, further motivating the importance our model ascribes to FD in shaping consumption patterns both for individual regions and the aggregate economy.

Table A2 reports the baseline results. In addition to the usual measurements of FD, we include two additional metrics for robustness: “DQ30 and CL80” calculates for each individual the portion of quarters in a year that they spent with either a credit card payment started in 2006.
Figure A3: Robustness to the year of pre-existing conditions

Notes: “30 day Delinquency of Any Type” gives the percentage of people in a zip code that are 30 or more days delinquent on any type of debt as recorded by the New York Federal Reserve Bank/Equifax CCP. “% of CC debt 30 days Delinquent” gives the percentage of all credit card debt in a zip code that is at least 30 days delinquent.

Sources: IRS SOI, Zillow, FRBNY Consumer Credit Panel/Equifax, Census Bureau, SCF. Each dot represents the mean of that bin of FD weighted by 2006 net wealth.

30 days delinquent or having reached 80 percent of their credit limit and then averages that percentage across the geography. “ADQ30” is defined much like DQ30, but gives the percentage of people in a zip code who are at least 30 days delinquent on any kind of debt recorded by the FRBNY/Equifax CCP. 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 FD. Comparing across columns suggests that our estimated coefficients are robust to the definition of FD we use. Importantly, the interaction term is positive: higher FD in 2002 is associated with larger consumption drops between 2006 and 2009.

32To give a clarifying example, say that there was an individual who in quarter 1 of 2002 was both at least 30 days delinquent on a credit card payment and had used over 80 percent of their available credit card limit. Then, in quarter 2, they remained over 80 percent 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 percent of the year in financial distress. Similar calculations would be made for all other individuals in our sample from their geography, and those numbers would be averaged to reach the final result.
Table A2: Auto spending at the zip-code level

<table>
<thead>
<tr>
<th>FD Measurement taken in 2002:</th>
<th>( \Delta_{06-09} ) Auto Spending</th>
<th>( \Delta_{06-09} ) Home Value</th>
<th>FD</th>
<th>( \Delta_{06-09} ) Home Value \times FD</th>
</tr>
</thead>
<tbody>
<tr>
<td>(DQ30) (CL80) (CL80 and DQ30) (ADQ30)</td>
<td>( \Delta_{06-09} )</td>
<td>Home Value</td>
<td>FD</td>
<td>Home Value \times FD</td>
</tr>
<tr>
<td>( \Delta_{06-09} ) Home Value</td>
<td>-0.005</td>
<td>-0.008</td>
<td>-0.009*</td>
<td>-0.006</td>
</tr>
<tr>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td></td>
</tr>
<tr>
<td>FD</td>
<td>-5.283***</td>
<td>-5.203***</td>
<td>-5.525***</td>
<td>-3.670***</td>
</tr>
<tr>
<td>(1.15)</td>
<td>(1.02)</td>
<td>(1.19)</td>
<td>(0.74)</td>
<td></td>
</tr>
<tr>
<td>( \Delta_{06-09} ) Home Value \times FD</td>
<td>0.099***</td>
<td>0.070***</td>
<td>0.097***</td>
<td>0.070***</td>
</tr>
<tr>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>14136</td>
<td>14136</td>
<td>14136</td>
<td>14136</td>
</tr>
</tbody>
</table>

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 zip code as of 2006. Standard errors appear in parentheses.

Given the results of Mian, Rao, and Sufi (2013), it may be worried that FD in these regressions is merely capturing variation in housing leverage. Figure 2 directly compares our baseline to the results controlling for the housing leverage ratio and Table A3 shows the corresponding regression output. The results for the interaction term of interest remain near unchanged for every measure of FD included, removing these concerns. Indeed, as shown in Figure A4, there does not appear to be any clear contemporaneous relationship between FD and housing leverage in 2002. Considering the 2006 housing leverage ratio against FD in 2002, there appears to be if anything a negative relationship between the two; i.e., regions with more financial distress tend to have lower leverage.

To mitigate the risk that their results stem from an omitted variable correlated with the decline in home prices, Mian, Rao, and Sufi (2013) instrument for changes in home value using housing supply elasticities from Saiz (2010). Our results are robust to these considerations as well, as shown in tables A4 and A5, where we present the first and second stages of the regression as we do in Table A2 but instead at the county level.

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, Rao, and Sufi (2013) and Aladangady (2017), among others. However, these results are not intended to establish a causal relationship between financial distress and observed consumption declines. Our model suggests that financial distress is a useful summary statistic capturing a history of high borrowing costs induced in part by individual impatience, which is difficult to observe directly. Rather, these results corroborate our model’s quantitative implications.
Table A3: Auto Spending at the Zip-code Level Controlling for Leverage

<table>
<thead>
<tr>
<th>FD Measurement taken in 2002:</th>
<th>$\Delta_{06-09}$ Auto Spending</th>
<th>(DQ30)</th>
<th>(CL80)</th>
<th>(DQ30 and CL80)</th>
<th>(ADQ30)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta_{06-09}$ Home Value</td>
<td>-0.012*</td>
<td>-0.013*</td>
<td>-0.015*</td>
<td>-0.013*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>FD</td>
<td>-5.458</td>
<td>-7.239*</td>
<td>-7.495*</td>
<td>-4.548*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.13)</td>
<td>(2.89)</td>
<td>(3.32)</td>
<td>(2.02)</td>
<td></td>
</tr>
<tr>
<td>$\Delta_{06-09}$ Home Value $\times$ FD</td>
<td>0.104***</td>
<td>0.068***</td>
<td>0.097***</td>
<td>0.073***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>Housing Leverage Ratio$_{06}$</td>
<td>-0.228</td>
<td>-1.216</td>
<td>-0.953</td>
<td>-0.677</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.15)</td>
<td>(1.69)</td>
<td>(1.48)</td>
<td>(1.18)</td>
<td></td>
</tr>
<tr>
<td>$\Delta_{06-09}$ Home Value $\times$ Housing Leverage Ratio$_{06}$</td>
<td>0.018*</td>
<td>0.014</td>
<td>0.016*</td>
<td>0.019*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>Housing Leverage Ratio, 2006 $\times$ FD</td>
<td>-0.320</td>
<td>4.519</td>
<td>4.164</td>
<td>1.637</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.69)</td>
<td>(6.16)</td>
<td>(7.11)</td>
<td>(4.37)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>14136</td>
<td>14136</td>
<td>14136</td>
<td>14136</td>
<td>14136</td>
</tr>
</tbody>
</table>

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 A4: Correlation of Housing Leverage (2002 and 2006) with FD (DQ30) in 2002

Notes: 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 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.
**Table A4:** First-Stage Regression, County-level data

<table>
<thead>
<tr>
<th>FD Measurement taken in 2002:</th>
<th>Δ₀₆−₀₉ Home Value</th>
<th>Δ₀₆−₀₉ Auto Spending</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(DQ30)</td>
<td>(CL80)</td>
</tr>
<tr>
<td>Saiz Elasticity</td>
<td>19.58***</td>
<td>19.90***</td>
</tr>
<tr>
<td></td>
<td>(1.80)</td>
<td>(1.80)</td>
</tr>
<tr>
<td>FD</td>
<td>109.420*</td>
<td>43.793</td>
</tr>
<tr>
<td></td>
<td>(52.50)</td>
<td>(51.03)</td>
</tr>
<tr>
<td>Observations</td>
<td>670</td>
<td>670</td>
</tr>
<tr>
<td>F</td>
<td>31.97</td>
<td>31.47</td>
</tr>
</tbody>
</table>

**Table A5:** Second Stage regression, County-Level

<table>
<thead>
<tr>
<th>FD Measurement taken in 2002:</th>
<th>Δ₀₆−₀₉ Home Value</th>
<th>Δ₀₆−₀₉ Auto Spending</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(DQ30)</td>
<td>(CL80)</td>
</tr>
<tr>
<td>Δ₀₆−₀₉ Home Value</td>
<td>-0.273*</td>
<td>-0.442**</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.16)</td>
</tr>
<tr>
<td>FD</td>
<td>-27.774</td>
<td>-23.662</td>
</tr>
<tr>
<td></td>
<td>(19.83)</td>
<td>(19.55)</td>
</tr>
<tr>
<td>Δ₀₆−₀₉ Home Value × FD</td>
<td>1.260*</td>
<td>1.304*</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td>(0.52)</td>
</tr>
<tr>
<td>Observations</td>
<td>670</td>
<td>670</td>
</tr>
</tbody>
</table>

Notes: 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.

**B Income Inequality**

Similar empirical results can be obtained looking at income inequality as the factor differentiating regions instead of FD.

First, note that our Facts 1 is about dispersion in FD across zip codes. Clearly, there is income inequality across zip codes, as shown in Figure A5.

Fact 2 is about the heterogeneity in the “aggregate” shocks so it doesn’t depend on income or FD. However, Fact 3 talks about the correlation of “aggregate shocks” and the incidence of FD. In Figure A6 shows this fact but now replacing FD with per household income. The two top figures show that the fact is also true for income per household. The bottom plot what it may be obvious: FD and income per household are very correlated. The correlation with FD is critical because this is what generates larger differences in MPCs.

Our analysis in the main body of the paper continues by making 5 quintiles of FD and calibrating an economy for each quintile. In Table A6 below we show that the quintiles would look similar if we made them according to income per household. To compare with FD quintiles it is useful to compare DQ30. Notice that when the quintiles are made according
to income per households, we find that DQ30 decreases from 20.3 percent to 10.8 percent. Obviously, the difference is larger when we made the quintiles according to DQ30 but the difference is not that significant. In that case DQ30 in Q1 is 8.6 and in Q2 is 23.5.

We could continue the analysis using quintiles of income to calibrate five economies and compute the quantitative results. However, we think that the numbers presented here are enough to conclude that we would obtain very similar results, perhaps slightly weaker because the difference in FD are a bit smaller.

C Recursive formulation of the 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:

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

where earnings are $e_n(z, \epsilon) = exp(f + l_n + z + \epsilon)$. Here $I_{rent}$ equals 1 when the household chooses 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:
Figure A6: Macro risks and income inequality
Change in house prices 2006-2012 and per household income 2002

Workers Leisure and Hospitality and per household income 2018

Relationship between financial distress and income, 2002
<table>
<thead>
<tr>
<th>Quintiles Of Income</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income Per Household $000</td>
<td>31.69</td>
<td>41.83</td>
<td>51.54</td>
<td>65.40</td>
<td>106.2</td>
</tr>
<tr>
<td>Net Wealth Per Hou. $000 SCF</td>
<td>82.86</td>
<td>116.8</td>
<td>144.3</td>
<td>191.7</td>
<td>415.6</td>
</tr>
<tr>
<td>Fin. Wealth Per Hou. $000 SCF</td>
<td>83.32</td>
<td>113.7</td>
<td>136.8</td>
<td>177.0</td>
<td>373.6</td>
</tr>
<tr>
<td>Net Fin. Wealth Per Hou. $000 SCF</td>
<td>48.22</td>
<td>67.07</td>
<td>78.61</td>
<td>101.7</td>
<td>266.5</td>
</tr>
<tr>
<td>Median Home Value $000</td>
<td>115.6</td>
<td>143.4</td>
<td>172.1</td>
<td>218.0</td>
<td>328.2</td>
</tr>
<tr>
<td>Less Than HS</td>
<td>25.79</td>
<td>19.57</td>
<td>15.93</td>
<td>11.23</td>
<td>7.113</td>
</tr>
<tr>
<td>HS</td>
<td>29.61</td>
<td>29.53</td>
<td>27.65</td>
<td>24.24</td>
<td>17.50</td>
</tr>
<tr>
<td>College</td>
<td>44.61</td>
<td>50.90</td>
<td>56.42</td>
<td>64.52</td>
<td>75.39</td>
</tr>
<tr>
<td>Age</td>
<td>42.75</td>
<td>43.06</td>
<td>43.24</td>
<td>43.47</td>
<td>44.12</td>
</tr>
<tr>
<td>Percent that Own a Home</td>
<td>56.71</td>
<td>64.23</td>
<td>69.31</td>
<td>74.59</td>
<td>78.08</td>
</tr>
<tr>
<td>Percent with Mortgage/HELOC Debt</td>
<td>29.26</td>
<td>36.13</td>
<td>40.68</td>
<td>46.11</td>
<td>50.22</td>
</tr>
<tr>
<td>Housing Debt per Home Owner $000</td>
<td>53.81</td>
<td>66.74</td>
<td>80.40</td>
<td>101.2</td>
<td>145.0</td>
</tr>
<tr>
<td>CC Debt Per Household $000</td>
<td>3.376</td>
<td>3.962</td>
<td>4.386</td>
<td>4.934</td>
<td>5.770</td>
</tr>
<tr>
<td>Housing Leverage</td>
<td>46.60</td>
<td>44.47</td>
<td>44.46</td>
<td>46.73</td>
<td>43.82</td>
</tr>
<tr>
<td>Percent with FD who have Mortgage/HELOC debt</td>
<td>23.52</td>
<td>26.84</td>
<td>29.28</td>
<td>31.66</td>
<td>33.99</td>
</tr>
<tr>
<td>Foreclosure Rate</td>
<td>2.999</td>
<td>2.498</td>
<td>2.288</td>
<td>1.939</td>
<td>1.759</td>
</tr>
<tr>
<td>Bankruptcy Rate</td>
<td>0.662</td>
<td>0.694</td>
<td>0.638</td>
<td>0.515</td>
<td>0.353</td>
</tr>
<tr>
<td>DQ30</td>
<td>20.27</td>
<td>18.15</td>
<td>16.32</td>
<td>13.71</td>
<td>10.80</td>
</tr>
</tbody>
</table>
\[ R_{j,n}(a, z, \epsilon) = \max \left\{ R_{j,n}^{P}(a, z, \epsilon), R_{j,n}^{BK}(a, z, \epsilon), R_{j,n}^{DQ}(a, z, \epsilon) \right\}, \tag{2} \]

and

\[ B_{j,n}(a, z, \epsilon) = B_{j,n}^{P}(a, z, \epsilon). \tag{3} \]

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 superscripts in each value function represent whether the household is, or is not, defaulting 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 has only to choose next period’s financial assets \( a' \):

\[ R_{j,n}^{P}(a, z, \epsilon) = \max_{a'} \quad u(c, h_R) + \beta_j \mathbb{E}\left[ N_{j,n-1}(a', z', \epsilon') | z \right] \tag{4} \]

\[ s.t. \quad c + q_{j,n}^a(h_R, 0, a', z) a' = e + a, \]

\[ e = \exp(f + l_n + z + \epsilon). \]

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:

\[ R_{j,n}^{BK}(a, z, \epsilon) = \quad u(c, h_R) + \beta_j \mathbb{E}\left[ N_{j,n-1}(0, z', \epsilon') | z \right] \tag{5} \]

\[ s.t. \quad c = e - \text{(filing fee)}, \]

\[ e = \exp(f + l_n + z + \epsilon). \]

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:

$$R_{j,n}^{DQ}(a, z, \epsilon) = u(c, h_R) + \beta_j E\left[\gamma N_{j,n-1}(0, z', \epsilon') + (1 - \gamma) N_{j,n-1}(a(1 + r_R), z', \epsilon')|z\right] \quad (6)$$

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

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

Here, $\gamma$ 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 an individual choosing to buy a house of size $h' \in \{h_1, \ldots, h_m\}$,

$$\hat{B}_{j,n}(a, z; h') = \max_{a',m'} u(c, h') + \beta_j E\left[H_{j,n-1}(h', m', a', z', \epsilon')|z\right] \quad (7)$$

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

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

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

$$B_{j,n}(a, z) = \max_{h' \in \{h_1, \ldots, h_H\}} \hat{B}_{j,n}(a, z; h'). \quad (8)$$

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 they 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:

\[
H_{j,n}(h, m, a, z, \epsilon) = \max \left\{ P_{j,n}(\cdot), F_{j,n}(\cdot), D_{j,n}(\cdot), S_{j,n}^B(\cdot), S_{j,n}^R(\cdot) \right\}
\]  

where:

\[
P_{j,n}(h, m, a, z, \epsilon) = \max \left\{ P_{j,n}^P(\cdot), P_{j,n}^{BK}(\cdot), P_{j,n}^{DQ}(\cdot) \right\},
\]

\[
F_{j,n}(h, m, a, z, \epsilon) = F_{j,n}^P(\cdot),
\]

\[
D_{j,n}(h, m, a, z, \epsilon) = \max \left\{ D_{j,n}^P(\cdot), D_{j,n}^{BK}(\cdot), D_{j,n}^{DQ}(\cdot) \right\},
\]

\[
S_{j,n}^B(h, m, a, z, \epsilon) = S_{n}^{B,P}(\cdot),
\]

\[
S_{j,n}^R(h, m, a, z, \epsilon) = S_{n}^{R,P}(\cdot).
\]

Notice that households that choose to refinance their mortgage cannot default on financial assets in any manner. Additionally, we model agents who elect to sell as having to 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:
\[ P^P_{j,n}(h, m, a, z, \epsilon) = \max_{a'} u(c, h) + \beta_j \mathbb{E} \left[ H_{j,n-1}(h', m(1-\delta), a', z', \epsilon') \big| z \right] \] (15)

\[ s.t. \quad c + q^*_n(h, m(1-\delta), a', z) a' = e + a - m, \]

\[ e = \exp(f + l_n + z + \epsilon). \]

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

\[ P^P_{BK}(h, b, a, z, \epsilon) = u(c, h) + \beta_j \mathbb{E} \left[ H_{j,n-1}(h', m(1-\delta), 0, z', \epsilon') \big| z \right] \] (16)

\[ s.t. \quad c = e - \text{filing fee} - m, \]

\[ e = \exp(f + l_n + z + \epsilon). \]

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

\[ P^P_{DQ}(h, m, a, z, \epsilon) = u(c, h) + \beta_j \mathbb{E} \left[ \gamma H_{j,n-1}(h', m(1-\delta), 0, z', \epsilon') \right] + (1 - \gamma) H_{j,n-1}(h', m(1-\delta), a(1 + r^R), z', \epsilon') \big| z \right] \] (17)

\[ s.t. \quad c = e - m, \]

\[ e = \exp(f + l_n + z + \epsilon). \]

**Mortgage refiner.** A household that refinances cannot default on financial assets \(a\) and must prepay their current mortgage, choose next period’s financial assets \(a'\), and choose the amount to borrow \(m'\) with their new mortgage:

\[ F^P_{P}(h, m, a, z, \epsilon) = \hat{B}_{j,n}(a + ph(1 + \xi_B) - q^*_n m + e_n(z, \epsilon); z; h) \] (18)
Note that 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 for 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 a mortgage is a utility cost $\Phi$, we can easily write this problem as the problem of a renter minus the utility cost of mortgage default:

$$D_{j,n}^P(h, m, a, z, \epsilon) = R_{j,n}^P(a, z, \epsilon) - \Phi.$$  \hspace{1cm} (19)

**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:

$$D_{j,n}^{BK}(h, m, a, z, \epsilon) = R_{j,n}^{BK}(a, z, \epsilon) - \Phi.$$  \hspace{1cm} (20)

**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:

$$D_{j,n}^{DQ}(h, m, a, z, \epsilon) = R_{j,n}^{DQ}(a, z, \epsilon) - \Phi.$$  \hspace{1cm} (21)

**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,

$$S_{j,n}^{RP}(h, m, a, z, \epsilon) = R_{j,n}^P(a + ph(1 - \xi_S) - q_n^*m, z, \epsilon).$$  \hspace{1cm} (22)

**Seller to other house.** This problem is just a special case of a homebuyer with cash on hand equal to earnings plus current financial assets plus gains/losses from selling the previous house,
\[ S_{J,j,n}^{p,b}(h, m, a, z, \epsilon) = B_{j,n}(a + ph(1 - \xi_S) - q_n^*m + e_n(z, \epsilon), z). \] (23)

\textbf{C.3 Mortgage prices}

When a household uses a mortgage that promises to pay \( m' \) next period, the amount it borrows is given by \( m'q_{m,n}^*(h', m', a', z, \epsilon) \), where:

\[ q_{j,n}^m(h', m', a', z) = \frac{q_{p,j,n}^m + q_{prepay,j,n}^m + q_{default,j,n}^m}{1 + r}. \] (24)

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

\[ q_{p,j,n}^m(h', b', a', z) = \rho_n \mathbb{E}[\text{mort pay, no def + mort pay, BK + mort pay, DQ}] | z, \]

with:

\[ \text{mort pay, no def} = \mathbb{I}_{P_{P,q-j,n-1}(h', m', a', z', \epsilon')} \left[ 1 + (1 - \delta)q_{j,n-1}^m(h', m', a'', z') \right], \] (26)

\[ a'' = a_{P,P,j,n-1}(h', m', a', z', \epsilon'), \]

\[ \text{mort pay, BK} = \mathbb{I}_{P^K_{p,j,n-1}(h', m', a', z', \epsilon')} \left[ 1 + (1 - \delta)q_{n-1}^m(h', m'', 0, z') \right], \] (27)

and

\[ \text{mort pay, DQ} = \mathbb{I}_{P^{DK}_{p,j,n-1}(h', m', a', z', \epsilon')} \left[ 1 + (1 - \delta) \times \left( \gamma q_{j,n-1}^m(h', m'', 0, z') + (1 - \gamma)q_{j,n-1}^m(h', m'', a'', z') \right) \right], \] (28)

with:

\[ a'' = (1 + rR) a' \text{ and } m'' = m'(1 - \delta). \]

Here, \( \rho_n \) is the age-specific survival probability and \( \mathbb{I} \) equals 1 whenever the corresponding
value function is the maximum of $P_{j,n-1}$.

Next, consider the price of prepayment tomorrow, $q_{\text{prepay}}$. This occurs when the household chooses to refinance or 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 $q^*$:

$$q_{\text{prepay},j,n}(h', m', a', z) = \mathbb{E}\left[\left(\mathbb{I}_{F_{j,n-1}(h', m', a', z', \epsilon')} + \mathbb{I}_{S_{j,n-1}(h', m', a', z', \epsilon')}\right)q^*_{j,n-1} \bigg| z\right].$$

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

$$q_{\text{default},j,n}(h', m', a', z) = \rho_n \mathbb{E}\left[\left(\mathbb{I}_{D_{j,n-1}(h', m', a', z', \epsilon')}\right) p h'(1 - \bar{\xi}_S) \bigg| \frac{m'}{m'}^z\right].$$

### 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:

$$q_{a,n}(h', m', a', z) = \frac{q_{\text{pay},j,n} + q_{\text{DQ},j,n}}{1 + r}. \tag{31}$$

First, consider the price of payment tomorrow, $q_{\text{pay}}$. This occurs in the following states: renter, no financial asset default; homebuyer, no financial asset default; mortgage payer, no financial asset default; mortgage refiner, 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,
\[ q_{\text{pay}, j, n}(h', m', a', z) = \rho_n \mathbb{E} \left[ \mathbb{I}_{R_{j, n-1}^P(a', z', \epsilon')} + \mathbb{I}_{B_{n-1}^P(a' + \epsilon_{n-1}(z', \epsilon'), z', \epsilon')} \right. \]
\[ + \mathbb{I}_{P_{j, n-1}^P(h', m', a', z', \epsilon')} + \mathbb{I}_{F_{j, n-1}^P(h', m', a', z', \epsilon')} \]
\[ + \mathbb{I}_{D_{j, n-1}^P(h', m', a', z', \epsilon')} + \mathbb{I}_{\mathbb{I}_{S_{j, n-1}^{R,P}(h', m', a', z, \epsilon') \mid z}} \].

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, \( q_{\text{DQ}} \). 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,

\[ q_{\text{DQ}, j, n}^a(h', m', a', z) = (1 - \gamma)(1 + r_R)\rho_n \mathbb{E} \left[ \mathbb{I}^P_{R_{j, n-1}(a', z', \epsilon')} \times q_{j, n-1}^a(h_R, 0, a'', z) \right. \]
\[ + \mathbb{I}^P_{P_{j, n-1}(h', m', a', z', \epsilon')} \times q_{j, n-1}^a(h_R, 0, a'', z') \]
\[ + \mathbb{I}^P_{D_{j, n-1}(h', m', a', z', \epsilon')} \times q_{j, n-1}^a(h', m'', a'', z') \mid z \]

with: \( a'' = (1 + r_R)a' \) and \( b'' = b'(1 - \delta) \).

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

### D Extra quantitative results

In this section we provide some additional details and results on the **no debt, ex-ante heterogeneous agents model with equal shocks** and the **no debt, ex-ante identical agents model with equal shocks**. As noted in the main text, both of these models impose a zero borrowing constraint, which effectively disallows the possibility of FD as we define it.

In the case of the **no debt, ex-ante heterogeneous agents model with equal shocks**, we
assume five different “regions” exist each with parameters following Table 4 but implicitly with the restriction that $\eta = 0.0$ as there is no FD. Because we assume equal shocks, each region is subject to the same distribution of shocks in the corresponding experiment.

The no debt, ex-ante identical agents model with equal shocks model is a simplified version of the previous one, with no heterogeneity in preferences and thus a single “region.” Relative to the previous model, this model only has two parameters to pin down: (1) the discount factor $\beta$, and (2) the size of rental houses $h^R$. We pick these parameters so this simplified model matches the savings/income ratio and home ownership rate of the third quintile of FD as reported in Table 3.

Figure A7 displays how consumption in these economies, along with the baseline model with equal shocks, respond to either house-price or income shocks. Focusing on house-price shocks and homeowners in panel (a), the different regions in baseline model respond more to house-price shocks as FD increases even when all regions are subject to the same sized shock. The no debt, ex-ante heterogeneous agent model captures this similar pattern in consumption responses, in spite of the lack of FD. However, this model understates the region-specific response by about 0.87ppt on average. The no debt, ex-ante identical agents model has only one region, but the response of this region is on average 0.91ppt smaller than any region in the baseline equal shocks economy. Thus, for the case of house-price shocks it appears that modeling FD alone is critical.

Turning to income shocks in panel (b) reveals even more striking differences across models. In this case the no debt, ex-ante heterogeneous agent model the response of consumption across quintiles closely resembles that of the baseline model with equal shocks, only underestimating the response by on average 0.30ppt. However, the model with no debt, ex-ante identical agents understates the response of consumption for any given quintile by nearly 2ppt. Comparing these three lines suggests ex-ante heterogeneity needed to match the distribution of FD is key in generating the consumption responses of the baseline economy.
Figure A7: Consumption Responses to Shocks by Quintile, Role of FD

(a) House-price shocks  
(b) Income shocks

Notes: All values are measured as percentage changes relative to the old steady state. In the housing shock case, these are average changes over three periods following the shock and it includes only homeowners. In the income shock case, the change is measured only in the period of the shock and it includes only workers. Solid lines represent the aggregate change across all quintiles.