Layoffs, Delinquencies, and the Credit Market*

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Preliminary and incomplete

March 20, 2025

Abstract

We examine how job layoffs pass-through into credit market. Using county-level data, we exploit how plausibly exogenous job layoff announcements translate into changes in credit card delinquencies. We find that for every 100 people affected by a layoff announcement, 10 more people become delinquent on credit cards. We then see how these empirical findings can be replicated in life cycle model of consumption and savings that features both unsecured debt and long-term mortgages. The model is rich enough to allow for delinquency and bankruptcy in both types of debt. We find the model can reasonably account for the observed empirical patterns. Additionally, the model allows us to study the substitution between different types of debt repudiation when a *layoff-like* shock arrives.

Keywords: Housing, Credit Card Debt, Recession, Bankruptcy, Foreclosure, Mortgage, Delinquency, Financial Distress, Forbearance.

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

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1 Introduction

Credit markets often serve as a barometer for broader economic conditions. Rising delinquencies on credit cards and other consumer loans frequently signal weak economic conditions, yet the mechanisms behind these shifts remain an open question. Layoffs, among the most disruptive economic shocks, have long been suspected to play a crucial role in driving credit delinquency. When workers lose jobs, income disruptions follow, altering consumption and debt repayment behavior. This paper seeks to quantify the effect of layoffs on consumer credit markets, providing both empirical estimates and a structural interpretation through a life cycle model of borrowing and default.

Using county-level data, we exploit plausibly exogenous job layoff announcements and track how these events translate into changes in credit card delinquency. The results indicate a substantial pass-through: for every 100 workers affected by a layoff announcement, an additional 10 individuals become delinquent on their credit card payments. Delinquency rates rise sharply in the first two quarters following layoffs, with effects that persist beyond the initial shock. These patterns emerge consistently across multiple specifications, whether in levels or first differences.

To interpret these findings, we develop a structural life-cycle model that incorporates unsecured debt and long-term mortgages, allowing for default and bankruptcy on both types of debt. This framework captures observed empirical patterns, demonstrating that workers facing layoffs adjust borrowing behavior and repayment decisions in predictable ways. Beyond matching the data, the model provides insights into substitution effects: when a *layoff-like* shock arrives, households shift between different forms of debt repudiation, navigating trade-offs between delinquency and bankruptcy.

The analysis leverages two primary data sources. First, the Credit Risk Insight Servicing McDash (CRISM) dataset, which brings together borrower-level credit records from Equifax and loan servicing data from McDash. CRISM offers a monthly panel that spans the years 2005 through 2020, encompassing detailed credit performance histories for a wide cross-section of U.S. borrowers. Its coverage accounts for roughly two-thirds of all active mortgage holders nationwide. Second, a novel web-scraped dataset of plant closures and layoffs provides precise identification of mass job losses. Combining these sources allows for a robust assessment of how layoffs influence debt repayment behavior at a granular geographic level.

The study of financial distress and default has been shaped by several key contributions. Models incorporating income and expenditure shocks to explain default behavior have been widely used, including the frameworks developed by Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007) and Livshits, MacGee, and Tertilt (2007). More recently, Athreya, Mustre-del Río, and Sánchez (2019) introduced heterogeneity in household discount rates to capture the persistence of financial distress.

The role of income shocks in mortgage default has been highlighted in empirical work by Gerardi, Ohanian, and Willen (2008) and Ganong and Noel (2020), showing that income declines rather than strategic behavior drives the majority of defaults. More closely related to this paper, Braxton, Herkenhoff, and Phillips (2021) documents the strong relationship between job loss and credit delinquency, finding that affected individuals delay debt payments for several months as a form of consumption smoothing.

Understanding the consequences of layoffs on credit markets is critical for both policymakers and financial institutions. By quantifying these effects and providing a structural interpretation, this study sheds light on the mechanisms linking job loss to financial distress. The findings highlight the importance of policies that mitigate the credit impact of layoffs, such as income support programs and debt forbearance measures, which may help curb delinquency spikes following economic disruptions.

2 Data

Credit Risk Insight Servicing McDash (CRISM)

To measure delinquencies, we use the Credit Risk Insight Servicing McDash (CRISM) dataset, which brings together borrower-level credit records from Equifax and loan servicing data from McDash. CRISM offers a monthly panel that spans the years 2005 through 2020, encompassing detailed credit performance histories for a wide cross-section of U.S. borrowers. Its coverage accounts for roughly two-thirds of all active mortgage holders nationwide.

This rich panel structure permits the measurement of delinquency status at a monthly frequency, enabling precise tracking of households' financial conditions over time. Because each borrower is observed in consecutive months, the dataset allows for the construction of county-level delinquency rates by aggregating individual outcomes to the geographic level of interest. Specifically, property addresses are used to place borrowers in the appropriate county, creating a county-month panel of delinquency counts and rates. CRISM's broad coverage and high-frequency updates make it particularly well-suited for studying local economic shocks.

By combining these county-level delinquency measures with information on plant closures, it becomes possible to analyze how localized disruptions in employment opportunities affect household financial health. The large sample size and extended time frame ensure that both larger metropolitan areas and smaller counties are represented, and that any relationships we uncover are robust to varying local economic conditions.

To construct the outcome variable at the county level, we collapse the borrower-level records to a quarterly county panel. Each mortgage is assigned to the county in which the underlying property is located, facilitating the aggregation of delinquency counts and the computation of delinquency rates. A borrower is classified as delinquent if any of their accounts is reported as at least 30, 60, 90, or 120 days past due during a given quarter. The dataset provides separate delinquency series for each threshold, allowing for a more granular analysis of financial distress. This structure enables us to distinguish between early-stage delinquencies (30 and 60 days past due) and more severe financial distress (90 and 120 days past due), capturing the progression of borrowers' repayment difficulties over time. We observe this delinquency levels across all U.S. counties in which there is nonmissing coverage, giving a final sample of about 120 million individuals in 1,632 counties per quarter.

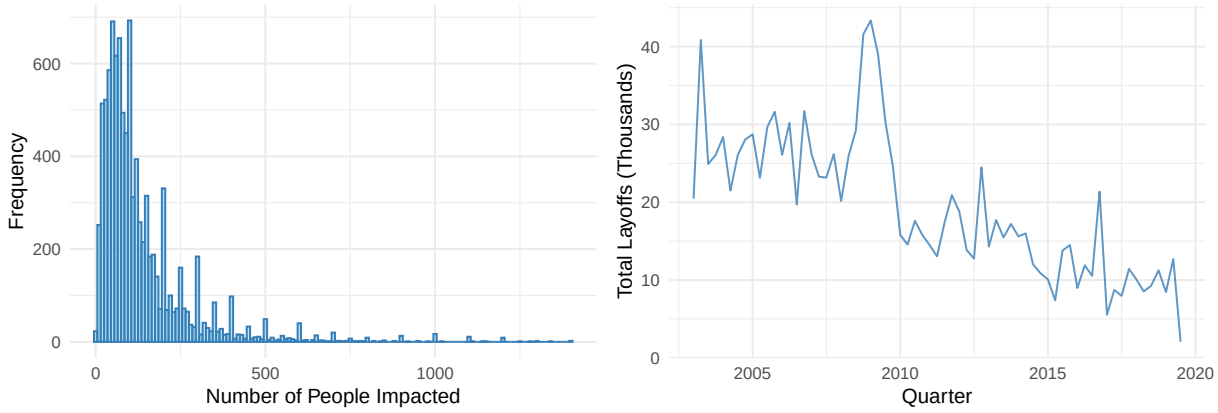
Plant Closures

USED BEFORE?? Our plant closures data consists of web-scraped data from publicly available sources, tracking plant closures and layoffs across various regions. It provides a structured record of employment disruptions by capturing key details such as the closure date, number of affected employees, geographic location, and industry sector of the closing business.

Each observation in the dataset corresponds to a specific plant or business that has ceased operations, allowing for precise identification of economic shocks at a local level. The closure date marks when the shutdown officially occurred, while the number of layoffs records the total number of workers impacted. The dataset also includes geographical identifiers, such as zip codes or broader regional classifications, enabling spatial analysis of closures. Furthermore, sector information categorizes each business by industry, facilitating an understanding of which economic sectors experience the most disruptions.

Given its high-frequency nature and broad geographic coverage, this dataset is well-suited for studying the effects of plant closures on labor markets, local economies, and financial outcomes such as delinquency rates. By linking these closures to other economic indicators, researchers can assess the short- and long-term impacts of job losses on affected populations. The dataset includes 9,549 recorded plant closure events, resulting in a total of 1,303,117 layoffs. On average, each closure leads to approximately 136 layoffs, though the distribution of job losses varies significantly. The median number of layoffs per event is 95, indicating that half of all closures result in fewer than 95 job losses, while the other half experience greater disruptions. The minimum recorded number of layoffs in a single event is 2, whereas the maximum reaches 1,400, highlighting the presence of both small-scale and large-scale employment shocks. The interquartile range further illustrates the dispersion in layoff sizes, with the 25th percentile (Q1) at 52 layoffs and the 75th percentile (Q3) at 165 layoffs.

Figure 1: Size Distribution and Quarterly Trends in Plant Closure Layoffs.

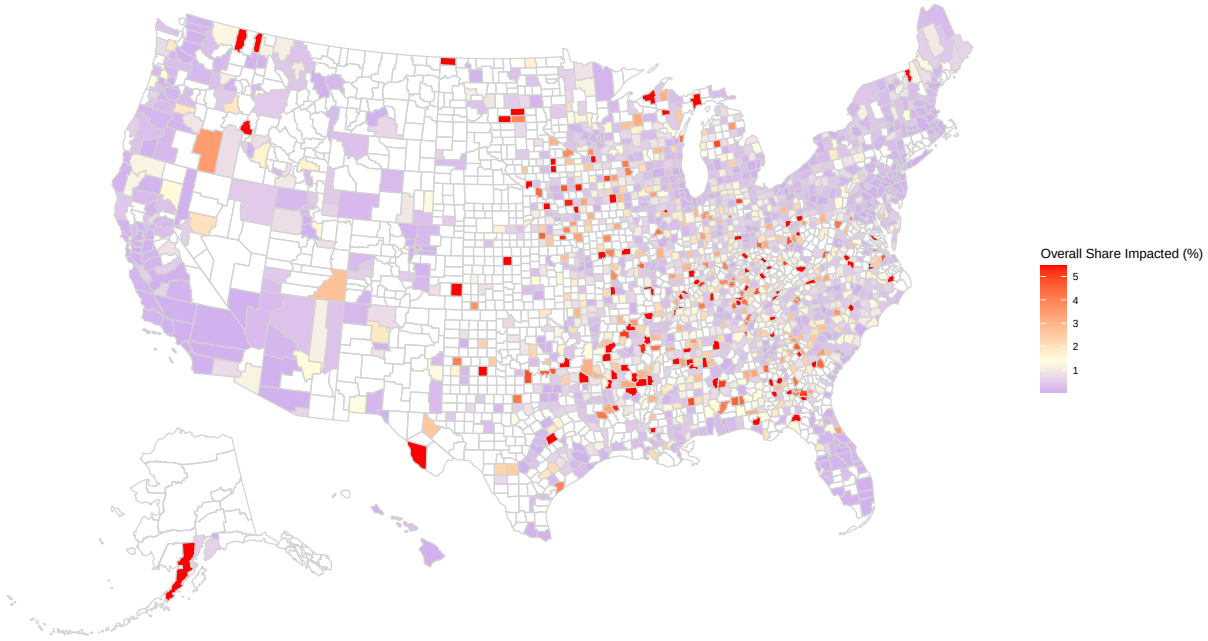


Source: FRB of Kansas City.

Figure 1 provides further insight into the distribution of plant closures and their aggregate trends over time. The left panel presents a histogram of the number of people impacted per plant closure event, revealing a highly skewed distribution. The majority of closures involve relatively small layoffs, with a sharp concentration of events affecting fewer than 200

workers. However, the presence of a long right tail indicates that some closures result in significantly larger employment disruptions, though these instances are less frequent. The right panel displays the total number of layoffs per quarter over time, reflecting clear fluctuations that align with broader economic cycles. In particular, layoffs spike around the period of the financial crisis, mirroring a severe but well-documented episode of macroeconomic distress. Beyond that exception, the observed variations appear to follow the general contours of normal economic activity, with no indication that these plant closures stem from unanticipated, noncyclical forces. Rather, they seem consistent with routine business cycles, sectoral shifts, and firm-level adjustments.

Figure 2: TBA



Source: CRISM and FRB of Kansas City. Shaded areas correspond to a 95% confidence level.

3 Empirical Analysis

This section investigates whether an increase in the number of individuals affected by a plant closure leads to higher delinquency rates at the county level. Rather than relying on a single reduced-form regression, we employ a local projections approach in the spirit of Jordà (2005), estimating the dynamic response of delinquencies at various horizons following a closure. This method is robust to potential misspecification of the underlying data-generating process and directly yields impulse-response-like estimates for the variable of interest.

Formally, for each horizon h, we estimate:

$$y_{i,t+h} = \alpha + \theta_h Z_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t,h}, \tag{1}$$

where $y_{i,t+h}$ denotes the delinquency measure in county i at time $t+h$. The variable $Z_{i,t}$ is the number of people impacted by the plant closure. County fixed effects γ_i account

for time-invariant characteristics specific to county i, whereas time-fixed effects δ_t capture broader macroeconomic shocks or seasonal factors common to all counties. Observations are weighted by the inverse of the county population in 2020, based on census data, to ensure that smaller counties—which may be especially vulnerable to a single plant closure—are not overshadowed by their larger counterparts.

The coefficient θ_h measures the within-county effect of an additional person impacted by a closure on the delinquency rate h periods in the future, holding other factors constant. A positive and statistically significant θ_h indicates that at horizon h, a rise in the number of affected individuals is followed by higher delinquency in that same county. By estimating this specification across multiple horizons, it becomes possible to map out the trajectory of delinquency responses over time and thus gain insights into both the immediate and more persistent consequences of local labor-market disruptions.

In constructing the delinquency measure, we aggregate all individuals who, within the previous three months, have had any account reach a worst payment status of at least 60 days past due.

In constructing the delinquency measure, we aggregate all individuals who, within the previous three months, have had any account reach a worst payment status of at least 60 days or 90 days past due.[1] This approach counts borrowers exhibiting either moderate or severe arrears in their credit records, thereby capturing a broader spectrum of distress than a narrower focus on 90-day delinquencies alone. By summing these cases to the county level, we obtain the delinquency levels that reflects recent serious payment difficulties, ensuring that shorter-term arrears and more severe delinquencies are included in the metric used for the empirical analysis. The analysis focuses on delinquencies up to 90 days past due, excluding 120-day delinquencies, as borrowers beyond this threshold are typically in default. By this stage, loans may be charged off, restructured, or transferred to collections, leading to data attrition that distorts the estimated effects. Consequently, movements at that stage would reflect a combination of true financial distress and borrowers exiting the dataset, making it a less reliable measure of the progression of delinquencies following plant closure.

Figure 3 presents the estimated impact of an increase in the number of individuals affected by a plant closure on the number of people entering 60-90 day delinquency (DQ6090) over different time horizons (h). The solid blue line represents the point estimates of θ_h, while the shaded region corresponds to the 95% confidence interval.

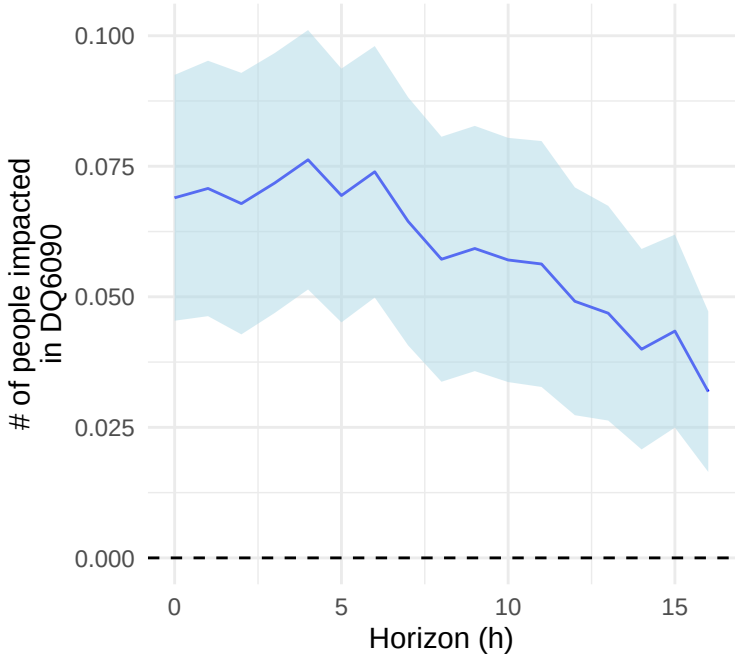
The results indicate that the effect of plant closures on delinquency is initially positive, with a peak around $h \approx 5 - 7$ quarters, suggesting that the number of affected individuals entering 60-90 day delinquency increases within a few months after a plant closure. This pattern is consistent with a delayed financial impact, where individuals facing job loss may rely on savings or temporary income sources before beginning to fall behind on payments.

After reaching its peak, the effect starts to decline gradually, with estimates trending downward beyond $h \approx 10$ quarters. This suggests that the rise in delinquencies is not permanent—some borrowers may recover financially, refinance their obligations, or transition into longer-term delinquency measures (such as 90+ days past due or foreclosure).

The confidence bands widen at longer horizons, reflecting increasing uncertainty in the estimates. This is expected due to fewer observations at longer lags and the potential influ-

[1]The impulse response functions for each delinquency stage are presented in Appendix A.

Figure 3: Dynamic Impact of Plant Closures on Delinquency Levels.



Source: CRISM and FRB of Kansas City. Shaded areas correspond to a 95% confidence level.

ence of additional economic factors over time. Overall, the results suggest a temporary but significant increase in the absolute number of delinquent individuals following plant closures, with the peak effect materializing within 5-7 quarters and gradually fading thereafter.

4 A Model of Housing Tenure, Delinquency, and Mortgage Delinquency

In this section, we outline the quantitative model used for our analysis. It builds on Mustre-del Río et al. (2025) by incorporating the possibility of mortgage delinquency. 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) and is in a similar vein to Mitman (2016).

4.1 Agents and Credit Markets

There is a continuum of finitely lived individuals who are risk averse and discount the future exponentially. All individuals face the risk of death in each period and survive to the next period with probability ρ_n, which depends on age n. Each agent works for a finite number of periods and then retires at age W. Critically, all agents are subject to risk in their income y (specified below). Lastly, agents will be 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 β_L, while the

remaining share has a discount factor of $\beta_H \geq \beta_L$.[2]

With respect to markets, households have (limited) access to credit and each period choose non-durable consumption c, housing h, mortgages m', and financial assets (or debt) a'. Households may choose to obtain housing services through homeownership or by renting.

Agents enter each period as either non-homeowners or homeowners. Rental houses are of size h_R. Owner-occupied houses vary in discrete sizes $h' \in \{h_1, h_2, \ldots, h_H\}$. To finance the purchase of 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.[3]

As described in greater detail below, agents can skip their mortgage payment for one period or default on their mortgage. If agents choose to default on their mortgage they immediately become renters. Alternatively, agents can skip their mortgage payment for one period and become non-current starting the next period, denoted by $s = 1$. In the next period, agents must pay the skipped mortgage payment plus an additional penalty κ; i.e. become current on their missed mortgage payment.

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 the 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 *not necessarily forgiven*, we allow for a probabilistic elimination of debts, with an i.i.d. probability η. 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.[4] 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.

4.2 Nonhomeowners

The options faced by a nonhomeowner with assets a and income y are represented in Figure 4. Nonhomeowners can choose to rent a house at price p_R, or they can buy a house and become a homebuyer. As can be seen from the tree, renting or purchasing a house each entail different decisions described below. For the sake of brevity, our formal description of

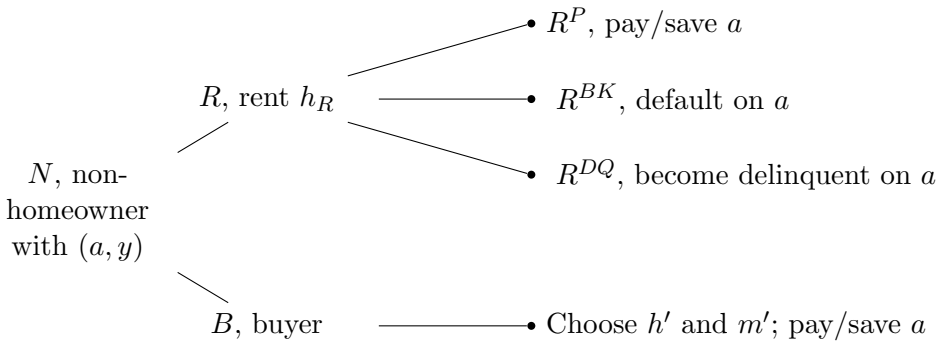
[2]Heterogeneity in the discount factor is common in macroeconomics at least since Krusell and Smith. (1998). However, the modeling and the calibration of β heterogeneity here follows closely Athreya et al. (2019).

[3]Housing choices, mortgages, and foreclosures are modeled as in Hatchondo et al. (2015).

[4]Athreya et al. (2017) analyze facts about informal default and introduced it to heterogeneous-agent models. Athreya et al. (2015) use this model to study the effect of the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005.

the recursive problems is presented in Appendix B.

Figure 4: Decision tree of a nonhomeowner



4.2.1 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

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

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: $c = y -$ (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

$$a' = \begin{cases} 0, & \text{with prob. } \eta, \\ (1 + r^R)a, & \text{with prob. } 1 - \eta. \end{cases} \tag{2}$$

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

4.2.2 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:

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

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

An important aspect of the bond and mortgage pricing functions is the last argument $s' = 0$. By definition, new homeowners enter tomorrow as current on their mortgage.

4.3 Homeowners

Compared to a renter, a homeowner's problem is more complex. The choices available to an existing homeowner are presented in Figure 5. 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, (v) become a renter, or (vi) delay their mortgage payment for one period. Each option is discussed below.

4.4 Making the mortgage payment

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

$$\begin{aligned} c + q^a_{j,n}(h, m(1-\delta), a', y, 0)a' = y + a - m - m_{-1}(1+\kappa)s. \\ s.t.\ \ m_{-1} = m/(1-\delta). \end{aligned} \tag{3}$$

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, the agent's discount factor type j, and the fact that tomorrow they enter as current ($s' = 0$) on their mortgage. The parameter δ captures the rate at which mortgage payments decay, which may happen, for example, because there is inflation and payments are fixed in nominal terms. The term $m_{-1}(1+\kappa)$ highlights that if the agent entered today as non-current, $s = 1$, on their mortgage, then they must repay last period's missed payment, m_{-1}, plus the penalty κ.

Agents who pay their mortgage but *formally default on unsecured debt* have the following budget constraint, $c = y - (\text{filing fee}) - m - m_{-1}(1+\kappa)s$, 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 $c = y - m - m_{-1}(1+\kappa)s$. Their financial debts tomorrow follow the same process as described under equation (2).

Figure 5: Decision tree of a homeowner



4.5 Skipping a mortgage payment

Homeowners can skip their mortgage payment for one period. However, by entering into mortgage delinquency they are flagged as being non-current on the mortgage for the next period, $s' = 1$, which can affect their borrowing rates. Additionally, when they enter the next period they must pay their missed payment in addition to a proportional cost κ. Thus, if they choose to become delinquent on their mortgage but pay their unsecured debt, they face the following budget constraint:

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

Notice that tomorrow's mortgage payment is still $m(1-\delta)$ as we enforce that immediately entering tomorrow, today's missed payment is made. Additionally, note that if the agent

enters today as non-current (so $s = 1$), then they must pay last period's missed mortgage payment.

Similarly, households who skip their mortgage payment and *informally default* on their unsecured debt consume $c = y - m_{-1}(1 + \kappa)s$. Their financial debts tomorrow follow the same process as described under equation (2).

4.5.1 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:

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

Here, $q^*_n m$ is the value of prepaying a mortgage of size m with n remaining periods worth of payments, which is:

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

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

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 renter who files for bankruptcy. Thus, the budget constraint is simply $c = y - filing\ fee$.

Lastly, we can write the problem of a mortgage defaulter who chooses delinquency as the problem of renter who is also delinquent on existing debt. This means that consumption is given by $c = y$ and financial assets tomorrow follow equation (2).

4.5.3 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:

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

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:

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

5 Model Calibration

In order to generate the quantitative results of the next section, we require taking a stance on model parameter values and the shocks fed into the model. The model calibration proceeds in two steps. First, we assign some parameters using external information. Second, we internally calibrate the remaining parameters so the model matches some key facts on the distribution of liquid wealth, housing tenure, financial distress, and mortgage forbearance.

5.1 Assigning first-stage parameters

Table 1 collects the parameters set externally. A period in the model refers to a quarter. Agents enter the model at age 25, retire at age 65, and die no later than age 82. We set the annual 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 β_H, or discount it more significantly (i.e., be "impatient") and use discount factor β_L. This heterogeneity allows the model to capture well the joint distribution of net financial wealth, delinquency (incidence and persistence), and bankruptcy. We set the discount factors so that annually β_H=1.00 and β_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 5.2.

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

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

where γ denotes the risk aversion parameter, α governs the degree of intra-temporal substitutability between housing and nondurable consumption goods, and θ determines the

expenditure share for housing. Following Hatchondo, Martinez, and Sánchez (2015), we set γ to 2, α to 0.5, and θ to 0.11.

Given these preferences and following Mustre-del Río, Mather, José, Sánchez, and Athreya (2025), we set the price of owner-occupied housing p to 3.3. This value generates median home value to income ratios between 3.2 and 3.3 as observed in the data. The size of rental houses, h_R, is calibrated internally and described in the next subsection.

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. Following Mustre-del Río, Mather, José, Sánchez, and Athreya (2025), we set the discharge rate of delinquent debt to match an annual rate of 25%. Following typical mortgage contracts, we set the penalty of skipping mortgage payments κ to 0.05.[5] Additionally, we allow for a utility cost of entering into mortgage delinquency Φ_{DQM}, to help the model match the level of mortgage delinquency observed in the data.

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

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

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

In retirement, the household receives a fraction of the last realization of the persistent component of its working-age income using the replacement ratio formula: $\max\{A_0 + A_1 exp(z^i_{W1}), A_2\}$. 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 the CDC National Vital Statistics for 2019.[6]

5.2 Estimating the remaining parameters

The only remaining parameters to pin down are the share of type-L individuals, s_L, the size of rental houses h^R, and the utility cost of being deliquent on mortgage payments, Φ_{DQM}. We estimate these parameters so that the model replicates a number of observations regarding wealth, homeownership, delinquency, and bankruptcy as observed in the data.

[5] See for example, https://www.unison.com/blog/homeownership/what-happens-after-late-mortgage-payment or https://www.lendingtree.com/home/mortgage/late-mortgage-payment/.

[6] See: https://ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/NVSR/70-19/Table01.xlsx.

Table 1: Externally Set Parameters

Parameter	Value	Definition	Basis
l	—	Life-cycle component of income	Kaplan and Violante (2010)
W	65	Retirement age	U.S. Social Security
ρ_n	—	Mortality age profile	CDC
a_0	—	Initial net financial asset distribution	SCF 1998-2016
σ^2_ϵ	0.063	Variance of ϵ	Kaplan and Violante (2010)
σ^2_e	0.0166	Variance of e	Kaplan and Violante (2010)
r	0.03	Risk-free rate	Standard
γ	2	Risk aversion	Standard
α	0.5	Elasticity of substitution	Standard
θ	0.11	Consumption weight of housing	Hatchondo, Martinez, and Sánchez (2015)
ξ_B	0.03	Cost of buying a house, households	Gruber and Martin (2003)
ξ_S	0.03	Cost of buying a house, households	Gruber and Martin (2003)
$\bar{\xi}_S$	0.22	Cost of selling a house, banks	Pennington-Cross (2006)
ξ_M	0.15	Cost of signing a mortgage	U.S. Federal Reserve
δ	0.02	Payments decay	Average inflation
A_0	0.7156	Replacement ratio	U.S. Social Security
A_1	0.04	Replacement ratio	U.S. Social Security
A_2	0.14	Replacement ratio	U.S. Social Security
λ	0.9	LTV limit	Positive down payment
$filing\ fee$	0.028	Cost of filing for bankruptcy/mean(inc)	Livshits, MacGee, and Tertilt (2007)
r_R	0.2	Roll-over rate on delinquent debt	Livshits, MacGee, and Tertilt (2007)
β_H	1.00	Discount factor of patient types	Athreya, Mustre-del Río, and Sánchez (2019)
β_L	0.80	Discount factor of impatient types	Athreya, Mustre-del Río, and Sánchez (2019)
p	3.33	Price of owner-occupied houses	See text
κ	0.05	Penalty for missed mortgage payment	See text
η	0.25	Annual discharge rate of delinquent debt	Mustre-del Río, Mather, José, Sánchez, and Athreya (202

As seen from Table 2, the model does a fairly successful job of matching salient facts about wealth, homeownership, bankruptcy, and delinquency, as observed in the data. Critically, it matches the relatively high level of unsecured credit delinquency, while matching comparatively lower rates of bankruptcy, mortgage default, and mortgage delinquency.

Table 2: Model Fit

	Data	Model
Savings/income	1.78	1.75
Homeownership*	68.76	61.00
Homeownership* age 30	42.67	0.00
Homeownership* age 40	61.40	75.76
Homeownership* age 50	75.19	88.92
Housing leverage	46.17	34.36
with housing debt*	39.83	31.28
with housing debt* / in FD	28.37	40.00
housing debt/income	1.57	1.02
Mortgage default rate*	2.24	0.10
Mortgage delinquency rate*	3.00	1.61
DQ rate*	15.43	14.15
BK rate*	0.63	1.34
Persistence of FD		
2 yrs	6.82	4.67
4 yrs	4.57	3.80
5 yrs	3.98	3.61
6 yrs	3.57	3.50
8 yrs	2.95	3.40
10 yrs	2.66	3.31

Notes: $*$ in percent. "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.

To generate the aforementioned patterns, the model requires the parameter estimates as reported in Table 3 .As can be seen in the first row, the model requires 39% of the population to be of type-L (i.e. impatient) in order to match the aforementioned facts. Additionally, given that the smallest house available for purchase is set to 1, the value of h^R suggests rental houses need to be somewhat attractive in order to match the homeownership rates observed in the data.

Table 3: Parameter Estimates

Parameter	Value
s_L	0.39
h_R	2.0
Φ_{DQM}	-0.03

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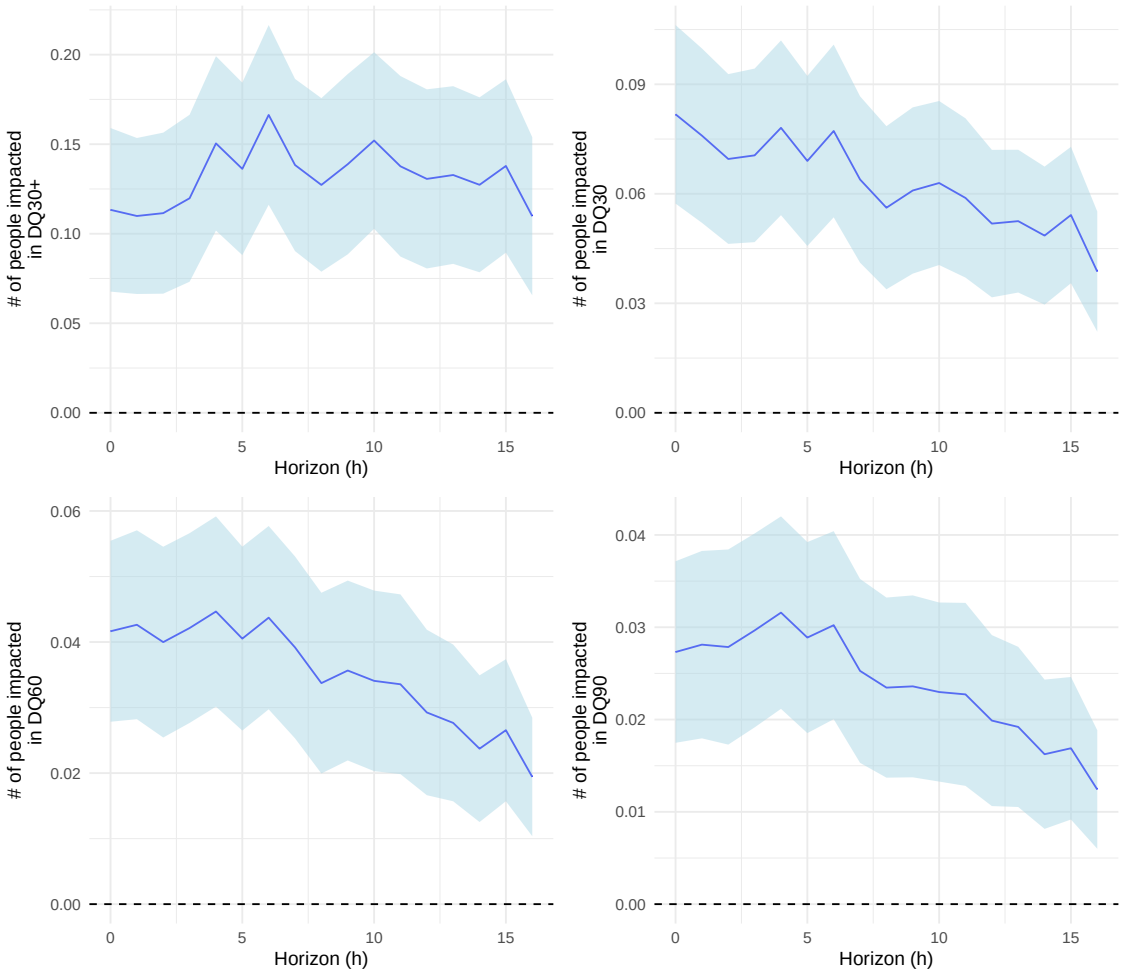
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Appendix

A Impulse Response Functions for Different Delinquency Stages

Figure A1: Dynamic Impact of Plant Closures on Delinquency Levels.



Source: CRISM and FRB of Kansas City. Shaded areas correspond to a 95% confidence level.

Following the specification outlined in Section 3, we extend the local projections (LP) model to examine the impact of plant closures on different stages of delinquency. Using the same empirical framework, we now estimate separate impulse response functions for borrowers at varying levels of financial distress, distinguishing between those with at least one account delinquent for 30 or more days (DQ30+), those who have missed payments for at least 60 days (DQ60), and those who have progressed to 90-day delinquency (DQ90).

The impulse response functions in Figure A1 trace the dynamic effects of plant closures on the number of individuals entering delinquency at different stages of severity. Each panel

corresponds to a distinct delinquency threshold, from 30-89 days past due (DQ30+, DQ60, DQ90). The solid line reports the estimated effect of an additional individual affected by a plant closure, while the shaded region represents the 95% confidence interval.

The results reveal a clear pattern: the number of individuals in delinquency rises following a plant closure, with notable differences across delinquency stages. The broadest measure, DQ30+, captures all borrowers with at least one account delinquent for 30 or more days. This series exhibits an immediate but temporary increase, reflecting the short-term financial strain experienced by many affected individuals. However, some borrowers recover before progressing into more severe delinquency. In contrast, DQ60 and DQ90 follow a more persistent trajectory, suggesting that a subset of borrowers struggles to regain financial stability and continues accumulating missed payments over time.

The results indicate that plant closures lead to a substantial but time-varying increase in delinquencies, with the peak impact materializing within the first several quartera and gradually fading thereafter. The widening confidence intervals at longer horizons reflect growing uncertainty in the estimates, likely due to the compounding influence of other macroeconomic shocks.

B Recursive formulation of the model

B.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:

$$N_{j,n}(a,z,\epsilon) = \max_{I_{rent}\in\{0,1\}} \left\{ I_{rent} R_{j,n}(a,z,\epsilon) + (1-I_{rent}) B_{j,n}(a + e_n(z,\epsilon), z) \right\}, \tag{4}$$

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:

$$R_{j,n}(a,z,\epsilon) = \max \left\{ R^{P}_{j,n}(a,z,\epsilon), R^{BK}_{j,n}(a,z,\epsilon), R^{DQ}_{j,n}(a,z,\epsilon) \right\}, \tag{5}$$

and

$$B_{j,n}(a,z,\epsilon) = B^{P}_{j,n}(a,z,\epsilon). \tag{6}$$

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':

$$\begin{aligned} R^P_{j,n}(a,z,\epsilon) = \max_{a'} \quad & u(c,h_R) + \beta_j \mathbb{E}\Big[N_{j,n-1}(a',z',\epsilon')|z\Big] \\ s.t. \quad & c + q^a_{j,n}(h_R,0,a',z)a' = e + a, \\ e \;\; = \;\; & exp(f + l_n + z + \epsilon). \end{aligned} \tag{7}$$

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:

$$\begin{aligned} R^{BK}_{j,n}(a,z,\epsilon) \;\; = \;\; & u(c,h_R) + \beta_j \mathbb{E}\Big[N_{j,n-1}(0,z',\epsilon')|z\Big] \\ s.t. \quad & c = e - (\text{filing fee}), \\ e \;\; = \;\; & exp(f + l_n + z + \epsilon). \end{aligned} \tag{8}$$

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:

$$\begin{aligned} R^{DQ}_{j,n}(a,z,\epsilon) \;\; = \;\; & u(c,h_R) + \beta_j \mathbb{E}\Big[\gamma N_{j,n-1}(0,z',\epsilon') + (1-\gamma)N_{j,n-1}(a(1+r^R),z',\epsilon')|z\Big] \\ s.t. \quad & c = e, \\ e \;\; = \;\; & exp(f + l_n + z + \epsilon). \end{aligned} \tag{9}$$

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

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

To simplify the problem later, consider a individual choosing to buy a house of size

$h' \in \{h_1 ....., h_m\}$,

$$\hat{B}_{j,n}(a, z; h') = \max_{a', m'} \quad u(c, h') + \beta_j \mathbb{E}\Big[H_{j,n-1}(h', m', a', z', \epsilon')|z\Big] \tag{10}$$

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

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

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

$$B_{j,n}(a, z) = \max_{h' \in \{h_1 ....., h_H\}} \hat{B}_{j,n}(a, z; h'). \tag{11}$$

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).

B.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:

$$H_{j,n}(h, m, a, z, \epsilon) \;\; = \;\; \max \left\{ P_{j,n}(\cdot), F_{j,n}(\cdot), D_{j,n}(\cdot), S^B_{j,n}(\cdot), S^R_{j,n}(\cdot) \right\} \tag{12}$$

where:

$$P_{j,n}(h, m, a, z, \epsilon) \;\; = \;\; \max \left\{ P^P_{j,n}(\cdot), P^{BK}_{j,n}(\cdot), P^{DQ}_{j,n}(\cdot) \right\}, \tag{13}$$

$$F_{j,n}(h, m, a, z, \epsilon) \;\; = \;\; F^P_{j,n}(\cdot), \tag{14}$$

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

$$S^B_{j,n}(h,m,a,z,\epsilon) = S^{B,P}_n(\cdot), \tag{16}$$

$$S^R_{j,n}(h,m,a,z,\epsilon) = S^{R,P}_n(\cdot). \tag{17}$$

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:

$$\begin{aligned} P^P_{j,n}(h,m,a,z,\epsilon) &= \max_{a'} \; u(c,h) + \beta_j \mathbb{E}\Big[H_{j,n-1}(h', m(1-\delta), a', z', \epsilon')|z\Big] \\ s.t. \qquad & c + q^a_{j,n}(h, m(1-\delta), a', z)a' = e + a - m, \\ & e = exp(f + l_n + z + \epsilon). \end{aligned} \tag{18}$$

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

$$\begin{aligned} P^{BK}_{j,n}(h,b,a,z,\epsilon) &= u(c,h) + \beta_j \mathbb{E}\Big[H_{j,n-1}(h', m(1-\delta), 0, z', \epsilon')|z\Big] \\ s.t. \qquad & c = e - \text{filing fee} - m, \\ & e = exp(f + l_n + z + \epsilon). \end{aligned} \tag{19}$$

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

$$\begin{aligned} P^{DQ}_{j,n}(h,m,a,z,\epsilon) &= u(c,h) + \beta_j \mathbb{E}\Big[\gamma H_{j,n-1}(h', m(1-\delta), 0, z', \epsilon') \\ &\quad + (1-\gamma) H_{j,n-1}(h', m(1-\delta), a(1+r^R), z', \epsilon')|z\Big] \\ s.t. \qquad & c = e - m, \\ & e = exp(f + l_n + z + \epsilon). \end{aligned} \tag{20}$$

Mortgage refinancer. 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:

$$F^P_{j,n}(h, m, a, z, \epsilon) = \hat{B}_{j,n}(a + ph(1 + \xi_B) - q^*_n m + e_n(z, \epsilon), z; h) \tag{21}$$

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 Φ, we can easily write this problem as the problem of a renter minus the utility cost of mortgage default:

$$D^P_{j,n}(h, m, a, z, \epsilon) = R^P_{j,n}(a, z, \epsilon) - \Phi. \tag{22}$$

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

$$D^{BK}_{j,n}(h, m, a, z, \epsilon) = R^{BK}_{j,n}(a, z, \epsilon) - \Phi. \tag{23}$$

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

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

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

$$S^{R,P}_{j,n}(h, m, a, z, \epsilon) = R^P_{j,n}(a + ph(1 - \xi_S) - q^*_n m, z, \epsilon). \tag{25}$$

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,

$$S^{P,B}_{j,n}(h, m, a, z, \epsilon) = B_{j,n}(a + ph(1 - \xi_S) - q^*_n m + e_n(z, \epsilon), z). \tag{26}$$

B.3 Mortgage prices

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

$$q_{j,n}^m(h', m', a', z) = \frac{q_{pay,j,n}^m + q_{prepay,j,n}^m + q_{default,j,n}^m}{1+r}. \tag{27}$$

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

$$q_{pay,j,n}^m(h', b', a', z) = \rho_n \mathbb{E}\Big[\text{mort pay, no def} + \text{mort pay, BK} + \text{mort pay, DQ} \Big| z\Big], \tag{28}$$

with:

$$\begin{aligned} \text{mort pay, no def} &= \mathbb{I}_{P_{j,n-1}^P(h',m',a',z',\epsilon')}\Big[1 + (1-\delta) q_{j,n-1}^m(h', m'', a'', z')\Big], \\ a'' &= \hat{a}_{j,n-1}^{P,P}(h', m', a', z', \epsilon'), \end{aligned} \tag{29}$$

$$\text{mort pay, BK} = \mathbb{I}_{P_{j,n-1}^{BK}(h',m',a',z',\epsilon')}\Big[1 + (1-\delta) q_{n-1}^m(h', m'', 0, z')\Big], \tag{30}$$

and

$$\begin{aligned} \text{mort pay, DQ} &= \mathbb{I}_{P_{j,n-1}^{DQ}(h',m',a',z',\epsilon')}\Big[1 + (1-\delta) \times \\ &\quad \Big(\gamma q_{j,n-1}^m(h', m'', 0, z') + (1-\gamma) q_{j,n-1}^m(h', m'', a'', z')\Big)\Big], \end{aligned} \tag{31}$$

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

Here, ρ_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_{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^*:

$$\begin{aligned} q_{prepay,j,n}^m(h', m', a', z) = &\\ &\mathbb{E}\Big[\Big(\mathbb{I}_{F_{j,n-1}(h',m',a',z',\epsilon')} \\ &+ \mathbb{I}_{S_{j,n-1}^R(h',m',a',z',\epsilon')} + \mathbb{I}_{S_{j,n-1}^B(h',m',a',z',\epsilon')}\Big) q_{j,n-1}^* \Big| z\Big]. \end{aligned} \tag{32}$$

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

$$q^m_{default,j,n}(h',m',a',z) = \rho_n \mathbb{E}\left[\frac{\left(\mathbb{I}_{D_{j,n-1}(h',m',a',z',\epsilon')}\right) ph'(1-\bar{\xi}_S)}{m'} \middle| z \right]. \tag{33}$$

B.4 Bond prices

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

$$q^a_{j,n}(h',m',a',z) = \frac{q^a_{pay,j,n} + q^a_{DQ,j,n}}{1+r}. \tag{34}$$

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

$$\begin{aligned} q^a_{pay,j,n}(h',m',a',z) = \rho_n \mathbb{E}\Bigg[& \mathbb{I}_{R^P_{j,n-1}(a',z',\epsilon')} + \mathbb{I}_{B_{n-1}(a'+e_{n-1}(z',\epsilon'),z',\epsilon')} \\ & + \mathbb{I}_{P^P_{j,n-1}(h',m',a',z',\epsilon')} + \mathbb{I}_{F^P_{j,n-1}(h',m',a',z',\epsilon')} \\ & + \mathbb{I}_{D^P_{j,n-1}(h',m',a',z',\epsilon')} \\ & + \mathbb{I}_{S^{R,P}_{j,n-1}(h',m',a',z',\epsilon')} + \mathbb{I}_{S^{B,P}_{j,n-1}(h',m',a',z',\epsilon')} \Bigg| z \Bigg]. \end{aligned} \tag{35}$$

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

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

$$
\begin{aligned}
q^a_{DQ,j,n}(h',m',a',z) = (1-\gamma)(1+r^R)\rho_n \mathbb{E}\Bigg[& \mathbb{I}_{R^{DQ}_{j,n-1}(a',z',\epsilon')} && \times \quad q^a_{j,n-1}(h_R,0,a'',z') \\
& +\mathbb{I}_{D^{DQ}_{j,n-1}(h',m',a',z',\epsilon')} && \times \quad q^a_{j,n-1}(h_R,0,a'',z') \\
& +\mathbb{I}_{P^{DQ}_{n-1}(h',b',a',z',\epsilon')} && \times \quad q^a_{j,n-1}(h',m'',a'',z')|z \Bigg] \\
\text{with:} \quad & a'' = (1+r^R)a' && \text{and} \quad b'' = b'(1-\delta).
\end{aligned} \tag{36}
$$

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