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Loan Delinquency Projections for COVID-19

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Grey Gordon
Federal Reserve Bank of Richmond

John Bailey Jones
Federal Reserve Bank of Richmond

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Grey Gordon
Federal Reserve Bank of Richmond

John Bailey Jones
Federal Reserve Bank of Richmond

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Abstract

We forecast the effects of the COVID-19 pandemic on loan delinquency rates under three scenarios for unemployment and house price movements. In the baseline scenario, our model predicts that loan delinquency rises from 2.3% in 2019 to a peak of 3.9% in 2025 with a total of $580B in write-offs. In 2021, absent policy intervention, the model predicts that delinquency would be 3.1%. However, mortgage forbearance, student loan forbearance, and fiscal transfers keep delinquency from increasing in 2021. The greatest reductions in delinquency are achieved through mortgage forbearance and student loan forbearance, with fiscal transfers playing a smaller role. In our adverse (favorable) scenario, loan delinquency peaks at 8.1% (2.8%) and write-offs total $1.1T ($420B).

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1 Introduction and main findings

In the text below, we describe a series of exercises that use data from the 2016 Survey of Consumer Finances (SCF) to project the incidence of loan delinquency or default in the near future. To make these projections, we assume that delinquency or default occurs when either of two financial ratios—the debt-service to income (DSY) ratio and the loan to value (LTV) ratio—exceed certain thresholds. We determine how many people will be above these thresholds by simulating DSY and LTV ratios for each SCF household under different unemployment and house price scenarios. Using this methodology, we also assess how well various policy proposals—fiscal transfers, student loan forbearance, and mortgage forbearance—mitigate the increases in delinquency and default (D-D). While these calculations cannot substitute for a complete economic model, they should provide reasonable first-pass estimates.

We consider three scenarios for the unemployment and house price shocks: a favorable case, a severe case, and an intermediate case. In the absence of policy interventions, we find the following:

1. When both shocks follow their intermediate trajectories, the D-D rate—measured as the fraction of debt 90+ days delinquent—rises from 2.3% in 2019 to 3.1% in 2021 and subsequently peaks at 3.9% in 2025. The delayed peak is due to persistence in house price decline. Total write-offs, absent policy intervention, end up being $580B.
2. When both shocks follow their worst-case trajectories, the D-D rate rises to 3.5% in 2021 and peaks at 8.1% in late 2025. Total write-offs end up being $1.1T.
3. When both shocks follow their most favorable trajectories, the D-D rate rises to 2.6% in 2021 and peaks at 2.8% in 2022. Total write-offs end up being $420B.

As model validation, we consider a "Great Recession" scenario where unemployment increases by 10 percentage points (our favorable case) and housing prices decline by 25% (our severe case). There we project an increase in D-D of 5.5 percentage points (pp). This matches fairly closely the 6.5pp increase found in the data, even though in our scenario unemployment peaks well before home prices bottom out, lowering the model's peak D-D rate.

The three policy interventions we analyze begin in the second quarter of 2020 and last for at most three years. Among the three policies we consider, the greatest reduction in the D-D rate is achieved by mortgage forbearance, then by student loan forbearance, and lastly by fiscal transfers. With all three policies in place, as they currently are under the Coronavirus Aid, Relief, and Economic Security (CARES) act, D-D rates and write-offs fall below their 2019 levels in the near term. It is important to note that, since we do not have a complete model, we cannot determine the true costs and benefits of these interventions.

2 Methodology

2.1 Overview

Our methodology is:

1. Use the 2016 SCF to calculate DSY and home LTV ratios for each household.
2. Assuming that delinquency or default occurs when these ratios exceed threshold values, find the thresholds that replicate the thresholds observed in the final quarter of 2019.
3. Develop several scenarios for how household income and home prices might respond to the coronavirus pandemic.
4. Under each scenario, recalculate the financial ratios and find the revised D-D rates.

2.2 Debt and Delinquency

Suppose that at date t, SCF household i has $d_{i,t}^{k}$ dollars of type-k debt. We will consider three classes of debt: credit card balances (CC), student loans (SL), and home mortgages (HM). The service cost associated with any sort of debt is the sum of the interest charges and principal repayments due at that time. To project debt service costs at any future date t, $s_{i,t}$, we hold the quantities of debt fixed at their 2019 value, but allow service rates to vary over time (due to policy changes):

$$s_{i,t} = R_t^{CC} d_{i,2019Q4}^{CC} + R_t^{SL} d_{i,2019Q4}^{SL} + R_t^{HM} d_{i,2019Q4}^{HM},$$

where R_t^k denotes the debt service rate for debt type k at date t.[1]

To calculate the DSY ratio, we divide the last four quarters of debt service payments by the last four quarters of income. Letting $y_{i,t}$ be quarterly income from the SCF,[2] the debt-service to income ratio, $dsy_{i,t}$, is

$$dsy_{it} = \frac{s_{i,t} + s_{i,t-1} + s_{i,t-2} + s_{i,t-3}}{y_{i,t} + y_{i,t-1} + y_{i,t-2} + y_{i,t-3}}.$$

[1] We assume the debt-service rate is identical across households.

[2] The SCF reports annual income, which divide by 4 to produce a quarterly measure.

We assume that a household goes delinquent or defaults on their credit card and/or student loan debt whenever its DSY ratio exceeds the cutoff value α. Letting $b_{i,t}$ be a 0-1 indicator of D-D on CC and SL debt, we have

$$b_{i,t} = \begin{cases} 1, \text{ if } dsy_{it} > \alpha, \\ 0, \text{ otherwise.} \end{cases}$$

For home mortgage debt (HM), we assume D-D occurs whenever households are significantly underwater on their mortgages. Let $P_t^{HM} a_{i,2019Q4}^{HM}$ denote the home's value as of date t. Here $a_{i,2019Q4}^{HM}$ is the value of household i's home in 2019Q4, and P_t^{HM} is the price of a home at date t **relative** to its price in 2019Q4. A household's loan-to-value ratio, $ltv_{i,t}$, is

$$ltv_{i,t} = \frac{d_{i,2019}^{HM}}{P_t^{HM} a_{i,2019}^{HM}},$$

We assume that mortgage D-D occurs whenever $ltv_{i,t}$ exceeds the cutoff value β **and** mortgage debt service is positive—a household cannot be delinquent if it does not need to service its debt.[3] Letting $f_{i,t}$ be a 0-1 indicator of HM default, we have

$$f_{i,t} = \begin{cases} 1, \text{ if } ltv_{i,t} > \beta \text{ and } R_t^{HM} > 0, \\ 0, \text{ otherwise.} \end{cases}$$

2.3 Simulation Dynamics

Our simulations start in the fourth quarter of 2019 and run through the second quarter of 2030. The dynamics in our simulations come from three sets of variables: the debt service charges R_t^{CC}, R_t^{SL} and R_t^{HM}; (relative) house prices P_t^{HM}; and individual incomes, $y_{i,t}$.

The dynamics of the debt service charges are simple. In the absence of loan forbearance, the charges equal their 2019 values, which we describe below; when there is loan forbearance, the charges for the affected loans are set to zero. The trajectories of relative house prices under our three scenarios, shown in the top panel of Figure 1, are somewhat more involved, but in all cases prices reach their lowest values in the fourth quarter of 2025. Prices fall by 5%, 15%, and 25% in the favorable, baseline, and severe scenarios; roughly, these are the declines from a mild recession, a bad recession, and the Great Recession.

[3]When a household is not underwater ($ltv_{i,t} < 1$), it makes little sense (ignoring closing costs) for it to default: the house can be sold, the mortgage paid off, and the equity kept. This is true even if debt-service costs are high, which is why we assume HM default occurs only in response to a high LTV ratio.

The dynamics of income are the most complicated. Each period a fraction of households are hit with unemployment shocks. Households hit by the shocks have their income fall by the proportion $(1-\theta)$. The "replacement rate" θ measures the extent to which unemployment benefits and other programs offset income losses in unemployment, and we set it to 50% based on recent estimates. In line with the recently passed CARES act, we also allow for the possibility that households receive transfers under a fiscal stimulus plan. We use T_t^e and T_t^u to denote transfers made to the employed and unemployed, respectively. Letting $u_{i,t}$ be a 0-1 unemployment indicator, income is given by

$$y_{i,t} = \begin{cases} y_{i,2019Q4} + T_t^e, & \text{if } u_{i,t} = 0, \\ \theta y_{i,2019Q4} + T_t^u, & \text{if } u_{i,t} = 1. \end{cases}$$

The dynamics of unemployment are as follows. Each unemployed household remains unemployed in the subsequent quarter with probability ρ and returns to work with probability $1-\rho$. We assume that ρ is constant over time. Households employed at date t transition into unemployment at date $t+1$ at the rate δ_t, which varies over time in accordance with the aggregate unemployment rate U_t.

The bottom panel of Figure 1 shows the trajectory of the aggregate unemployment rate under our three scenarios. Unemployment peaks at 10%, 20% and 30% in the favorable, baseline, and severe scenarios, respectively.

3 Model Inputs

In this section we document how we set the inputs for the model. Readers uninterested in these details should skip to the results in section 4.

3.1 Household data

The household data come from the 2016 wave of the Survey of Consumer Finances. We include families in the sample if their income was at least $10,000 and their debts (credit card, student loans, mortgages) totaled at least $1,000. Households older than 65 are dropped, as they do not have much debt and are unlikely to be affected by changes in the aggregate unemployment rates. With these restrictions, our initial sample of 31,240 families drops to 15,009.

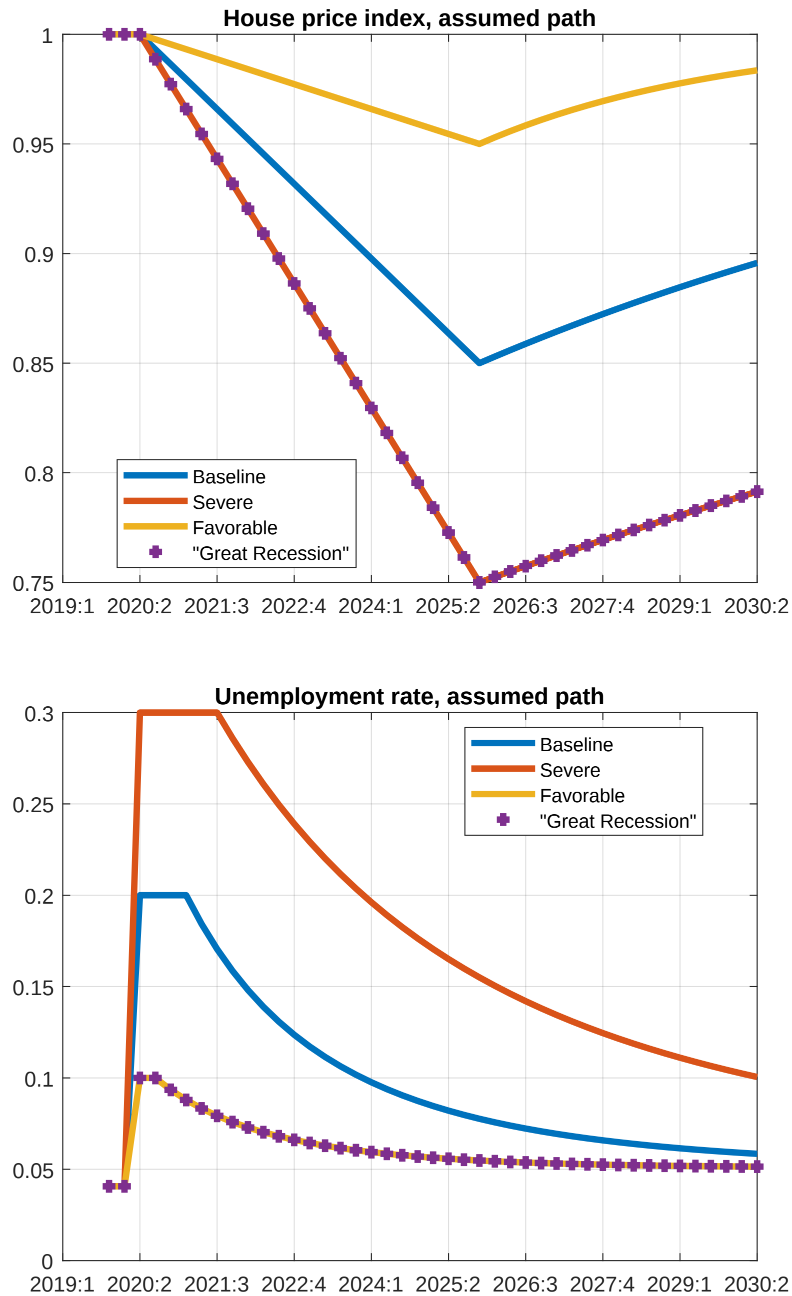

Figure 1: Unemployment rates and house prices by scenario

3.2 Debt service and delinquency

The debt service charges in the pre-COVID baseline are set as follows:

Debt class	Service costs R^k_{2019Q4}	Explanation
Student loans	.0335	3.4% interest with 10% paid off annually. This is a .134 debt service rate annually, .0335 quarterly.
Mortgage	.0183	4% interest with 3.33% paid off annually. This is a .0733 debt service rate annually, .0183 quarterly.
Credit card	.04	16% interest with 0% paid off annually. This is a .04 quarterly rate.
Other debts	0	Other debts omitted.

Table 1: Debt service charges

We set the delinquency cutoff for the DSY ratio, α, so that the fraction of CC and SL debt that is delinquent (the debt-weighted average of $b_{i,2019Q4}$) is 10.0%, which is the 90+-days-late delinquency rate for combined CC and SL balances.[4] This yields $\alpha = 0.495$.

We set the default cutoff for the LTV ratio, β, so that the fraction of HM debt in default (the debt-weighted average of $f_{i,2019Q4}$) is 1.07%, the 90+-days-late delinquency rate for mortgage balances reported for that date.[5] This yields $\beta = 1.26$. This implies households must be **significantly** underwater in order to default, which is due at least in part to the high transaction costs of selling a home (typically around 7%).

3.3 Aggregate unemployment dynamics

Recall that the probability that an unemployed household remains unemployed is ρ, while the transition rate from employment to unemployment is given by a separation rate / job destruction rate of δ_t. Given these transition rates for individuals, we have the following laws of motion for unemployment U_t and employment E_t:

$$U_{t+1} = \delta_t E_t + \rho U_t,$$
$$E_{t+1} = (1 - \delta_t) E_t + (1 - \rho) U_t,$$

As shown in the top panel of Table 2, ρ is chosen to match either a 20-, 30-, or 40-week average duration of unemployment, depending on the scenario. Then given a path for unemployment,

[4] Authors' calculations using data from the Federal Reserve Bank of New York's Quarterly Report on Household Debt and Credit, available here, with the underlying data available here.

[5] See Figure 12, "Percent of Balance 90+ Days Delinquent by Loan Type", of the report available here.

$\{U_t\}$, we infer the separation rate as

$$\delta_t = \frac{U_{t+1} - \rho U_t}{E_t}.$$

For aggregate unemployment, we assume that 2020Q2 unemployment reaches a peak of $U_{\max}$, stays there for τ^U periods, and subsequently reverts to its long-run average at a rate ϕ^U. Specifically, after the peak we assume $\ln(U_t) = (1 - \phi^U)\mu^U + \phi^U \ln(U_{t-1})$. In our severe scenario, we take $U_{\max} = 30\%$, $\tau^U = 6$ (i.e., six quarters), and use the estimated mean and persistence $(\mu^U, \phi^U) = (1.627, 0.973)$. While 30% would indeed be severe, St. Louis Fed President James Bullard notably mentioned the possibility.[6] In our baseline, we assume maximum unemployment of 20% lasting for four quarters, and we allow for a faster recovery by using $\phi^U = 0.94$. The favorable case has an even smaller and shorter-lived dip, $U_{\max} = 10\%$, $\tau^U = 2$, with an even faster recovery of $\phi^U = 0.9$. The scenarios are summarized in Table 2.

Scenario	Inputs	Description
Unemployment		
Baseline	$U_{\max} = 0.20, \phi^U = 0.94, \tau^U = 4, \rho = 0.5833$	Peak unemployment 20% lasting 4 quarters, medium recovery, average individual unemployment duration 30 weeks
Favorable	$U_{\max} = 0.10, \phi^U = 0.9, \tau^U = 2, \rho = 0.3750$	Peak unemployment 10% lasting 2 quarters, fast recovery, average individual unemployment duration 20 weeks
Severe	$U_{\max} = 0.30, \phi^U = 0.973, \tau^U = 6, \rho = 0.6875$	Peak unemployment 30% (Bullard estimate) lasting 6 quarters, slow recovery, average individual unemployment duration 40 weeks
Housing		
Baseline	$P^{HM}_{\min} = 0.85$, $\phi^{HM} = 0.98$, $\tau^{HM} = 22$	Half-life recovery time from peak-to-trough in Great Recession
Favorable	$P^{HM}_{\min} = 0.95$, $\phi^{HM} = 0.95$, $\tau^{HM} = 22$	Small dip, fast recovery
Severe	$P^{HM}_{\min} = 0.75$, $\phi^{HM} = 0.99$, $\tau^{HM} = 22$	AR(1) estimated on log real house price index is 0.998 (even more persistent)

Table 2: Unemployment and housing scenarios

[6] See https://www.bloomberg.com/news/articles/2020-03-22/fed-s-bullard-says-u-s-jobless-rate-may-soar-to-30-in-2q.

3.4 House price dynamics

To model house price dynamics, we turn to the last recession to get realistic measures of peak-to-trough movements and recovery rates. We begin by setting $P^{HM}_{2020Q2} = P^{HM}_{2020Q1} = P^{HM}_{2019Q4} = 1$. From that point, home prices fall linearly for the next τ^{HM} quarters, reaching the trough value of $P^{HM}_{\min}$. After reaching the trough, we assume the price reverts to the 2019Q4 value at the gross rate ϕ^{HM}. Formally,

$$P^{HM}_t = \begin{cases} 1, & \text{if } t \leq 2020Q2, \\ 1 + \dfrac{t - 2020Q2}{\tau^{HM}}(P^{HM}_{\min} - 1), & \text{if } t \in \{2020Q2, \ldots, 2020Q2 + \tau^{HM}\}, \\ (P^{HM}_{t-1})^{\phi^{HM}}, & \text{if } t > 2020Q2 + \tau^{HM}. \end{cases}$$

The bottom panel of Table 2 describes $(P^{HM}_{\min}, \phi^{HM}, \tau^{HM})$ for each of our scenarios.

3.5 Policy interventions

Recall that income follows

$$y_{i,t} = \begin{cases} y_{i,2019Q4} + T^e_t, & \text{if } u_{i,t} = 0, \\ \theta y_{i,2019Q4} + T^u_t, & \text{if } u_{i,t} = 1, \end{cases}$$

where θ is the replacement rate for households with an unemployed member, and T^e_t and T^u_t are government transfers. We set θ to 0.5, based on a recent micro-simulation analysis by the Urban Institute.[7] Table 3 summarizes the policy interventions.

Abbreviation	Policy	Parameters
NP	No additional policy intervention	$\theta = 0.5$, $T^e_t = 0$, $T^u_t = 0$
FP	Fiscal stimulus	$\theta = 0.5$, $T^e_{2020Q2} = 1200$, $T^u_{2020Q2} = 9600 + 1200$
SLP	Student loan forbearance	$R^{SL}_{2020Q2:2023Q2} = 0$
MP	Mortgage forbearance	$R^{HP}_{2020Q2:2023Q2} = 0$

Table 3: Policy experiments

[7] The study is available at www.urban.org/sites/default/files/publication/25461/412580-What-Happens-to-Families-Income-and-Poverty-after-Unemployment-.PDF.

4 Projections

4.1 Baseline projections with policy outcomes

Figure 2 shows how the aggregate delinquency rate—measured as the fraction of total debt that is delinquent—evolves over time in the baseline scenario, where both unemployment and housing prices follow their intermediate trajectories. In the absence of any countervailing policies, delinquency rates peak at about 3.9% at the end of 2025, and write-offs reach $580 billion. The peak in delinqency coincides with the trough of house prices; by this date, unemployment has largely returned to its baseline value (see Figure 1). Even though housing prices have the larger effect, in the nearer term unemployment raises delinquency as well. This can best be seen in the delinquency rate for the sum of credit card and student loan debt in Table 4, which rises from 10.0% to 13.2%. Because HM debt ($9.56T in 2019Q4) is about four times larger than the sum of CC and SL debt ($2.44T), the overall delinquency rate most closely tracks the delinquency rate for HM debt.

Figure 2 and Table 4 also show the effects of the policy interventions. As the policies we evaluate all stop before 2025, the peak delinquency rates are invariant to policy. However, in the nearer term, the policies lead to significantly lower delinquency rates. Mortgage forbearance generates the largest decreases, but student loan forbearance has significant effects as well. Both of these interventions push delinquency below its baseline rate, as they cover households that would have been delinquent even in the absence of coronavirus-related shocks. The effects of the fiscal stimulus are considerably smaller. It bears noting that in the absence of a complete model, we cannot determine the true costs and benefits of these interventions. To give just one example, policies that offset income losses or reduce delinquency may also dampen the fall in house prices.

4.2 Severe and favorable projections with policy outcomes

Figure 3, along with the bottom two panels of Table 4, assesses two alternative scenarios. Here we assume that the unemployment and house price trajectories are correlated: higher rates of unemployment are accompanied by larger declines in house prices. The top panel of Figure 3 illustrates the most severe scenario, where delinquency rates climb to 8.1% and write-offs reach more than $1 trillion. The bottom panel shows the most favorable alternative, where delinquency rates never reach 3% and write-offs reach a maximum of $420 billion. It is worth noting that in every scenario, when all three policies are enacted—as they now have been—write-offs drop to essentially zero in 2021. Hence, in the near term we do not expect

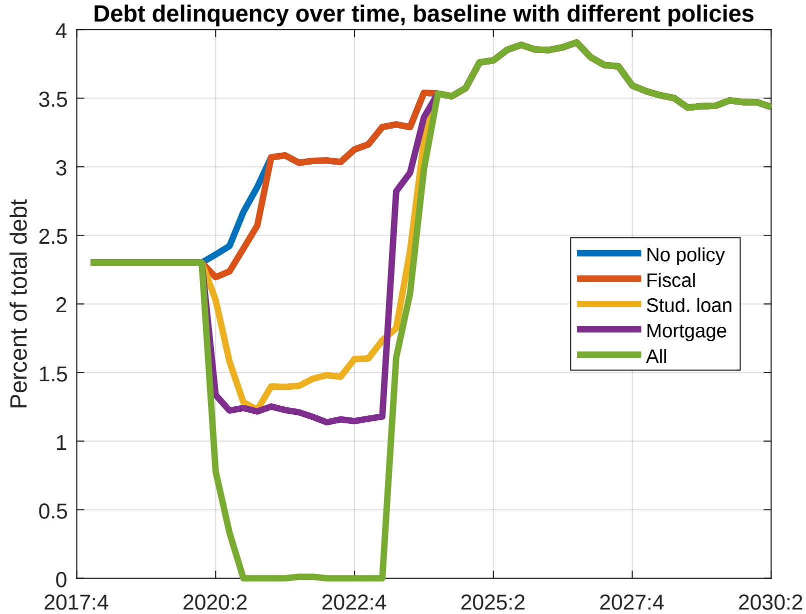

Figure 2: Delinquency paths in the baseline scenario

Scenario		Policy intervention			Percentage of debt delinquent						Write-offs	
					Average in 2021			Peak			USD Trillions	
Unemp.	Housing	FP	SLP	MP	All	$CC + SL$	HM	All	$CC + SL$	HM	2021	Total
Baseline	Baseline				3.1	13.2	1.4	3.9	13.2	2.7	0.46	0.58
Baseline	Baseline	Yes			3.1	13.2	1.4	3.9	13.2	2.7	0.46	0.58
Baseline	Baseline		Yes		1.4	1.3	1.4	3.9	11.7	2.7	0.17	0.54
Baseline	Baseline			Yes	1.3	8.9	0.0	3.9	11.7	2.7	0.22	0.54
Baseline	Baseline	Yes	Yes	Yes	0.0	0.1	0.0	3.9	11.7	2.7	0.00	0.54
Severe	Severe				3.5	14.9	1.7	8.1	14.9	7.3	0.52	1.06
Severe	Severe	Yes			3.5	14.9	1.7	8.1	14.9	7.3	0.52	1.06
Severe	Severe		Yes		1.7	1.8	1.7	8.1	13.3	7.3	0.20	1.02
Severe	Severe			Yes	1.4	10.1	0.0	8.1	13.3	7.3	0.25	1.02
Severe	Severe	Yes	Yes	Yes	0.0	0.1	0.0	8.1	13.3	7.3	0.00	1.02
Favorable	Favorable				2.6	11.5	1.2	2.8	11.5	1.5	0.39	0.42
Favorable	Favorable	Yes			2.6	11.5	1.2	2.8	11.5	1.5	0.39	0.42
Favorable	Favorable		Yes		1.1	0.9	1.2	2.8	11.1	1.5	0.13	0.41
Favorable	Favorable			Yes	1.1	7.7	0.0	2.8	11.1	1.5	0.19	0.41
Favorable	Favorable	Yes	Yes	Yes	0.0	0.0	0.0	2.8	11.1	1.5	0.00	0.41

Note: For the definitions of MP, SLP, and FP, see Table 3; "All" debt refers to $HM + CC + SL$.

Table 4: Projections by scenario and policy

delinquency rates to rise substantially, despite the large disruptions.

4.3 Model validation: comparison with the Great Recession

A natural question to ask is how well our methodology would do at predicting outcomes in the Great Recession, where unemployment rose to 10% and house prices fell by 25%. To assess this in a simple way, we assume unemployment follows its favorable scenario and house prices follow their severe scenario.

Figure 4 shows how D-D rates rise and fall during the Great Recession period, for both the data and the model. Overall, the data and model D-D series show similar increases and similar overall patterns. D-D rates rise sooner in the model than in the data. This is because in the data, the unemployment peak and the house price trough were only two years apart,[8] whereas in the model we assume that unemployment peaks immediately while house prices reach their minimum five years later. We think that this is a reasonable difference, given the swift onset of the coronavirus shock, as opposed to the somewhat slower progression of the Great Recession. Taking these considerations into account, we think the model performs very well.

4.4 Sensitivity analyses

While we have established that declining home prices lead to larger increases in delinquency, and are for the most part responsible for its peak value, we have not fully disentangled their effects from those of higher unemployment. Table 5 takes a step in this direction. The top panel of the table shows the effects of each unemployment scenario, holding the home price trajectory at its baseline. Moving from the baseline to the severe unemployment scenario raises the total delinquency rate in 2021 by 0.2pp; moving to the favorable scenario lowers the rate by 0.3pp. These effects are larger than the near-term (2021) effects of changing the house price trajectory, as shown in the table's bottom panel. Specifically, moving from the baseline to the severe housing scenario raises the 2021 D-D rate by 0.1pp; moving to the favorable housing scenario lowers the rate by 0.2pp.

Recall that, in the absence of loan forbearance, interest rates are held fixed throughout our projections. We therefore do not account for the possibility that, say, interest rates will rise as the economy recovers from the pandemic. Most home mortgages and student loans are fixed-rate, implying that changes in interest rates affect service costs only for new borrowers. We explored the consequences of raising the nominal credit card rate by 3pp annually at different

[8]In the Great Recession, unemployment (FRED series UNRATE) peaked in late 2009 and house prices reached their trough two years later (FRED series USSTHPI).

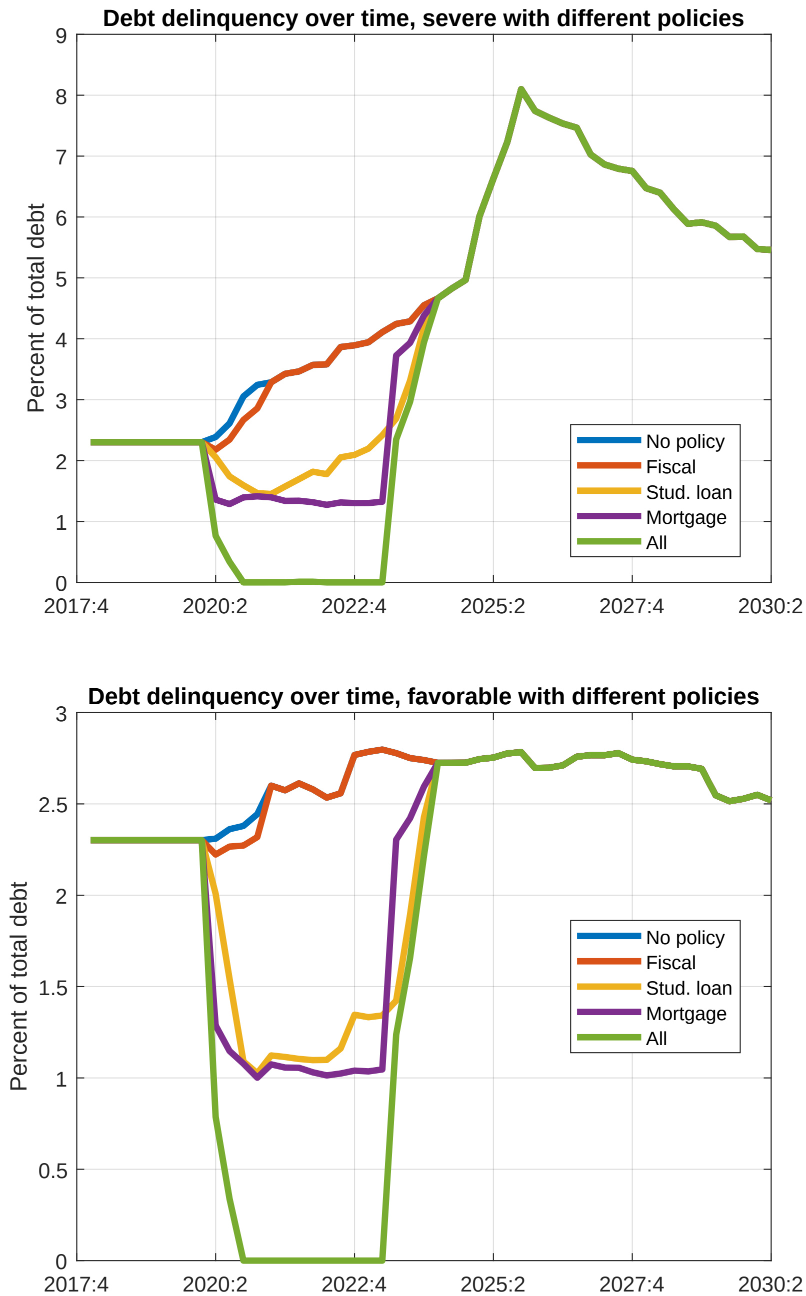

Figure 3: Delinquency paths in the alternate scenarios

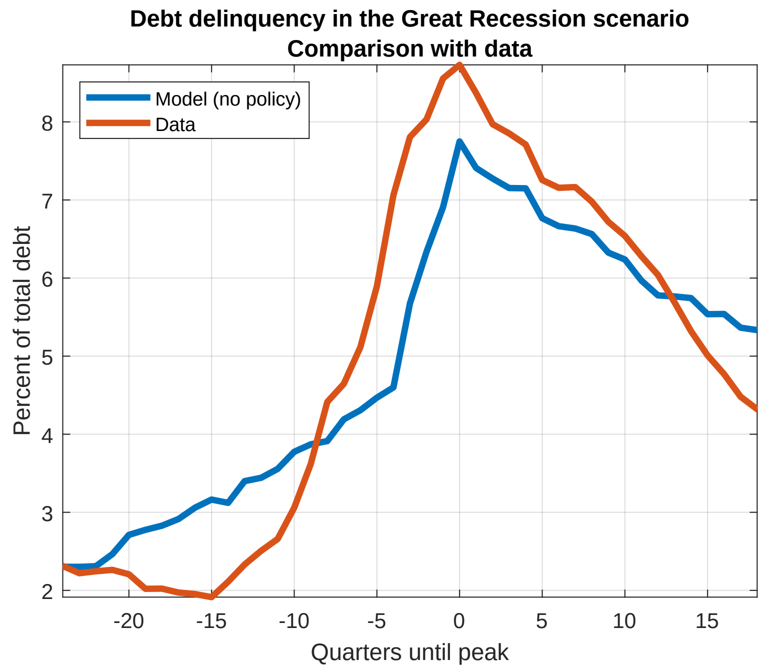

Figure 4: Comparison of model “Great Recession” scenario with the data

Scenario		Percentage of debt delinquent						Write-offs	
		Average in 2021			Peak			USD Trillions	
Unemp.	Housing	All	$CC + SL$	HM	All	$CC + SL$	HM	2021	Total
Unemployment varies, housing fixed at baseline									
Baseline	Baseline	3.1	13.2	1.4	3.9	13.2	2.7	0.46	0.58
Severe	Baseline	3.3	14.9	1.4	4.2	14.9	2.7	0.50	0.62
Favorable	Baseline	2.8	11.5	1.4	3.8	11.5	2.7	0.42	0.54
Housing varies, unemployment fixed at baseline									
Baseline	Baseline	3.1	13.2	1.4	3.9	13.2	2.7	0.46	0.58
Baseline	Severe	3.2	13.2	1.7	7.8	13.2	7.3	0.48	1.02
Baseline	Favorable	2.9	13.2	1.2	3.0	13.2	1.5	0.43	0.47

Note: For the definitions of MP, SLP, and FP, see Table 3; “All” debt refers to $HM + CC + SL$.

Table 5: Projections by unemployment or housing scenario, holding the other fixed, and policy

points in the next few years. Because credit card debt is a small component of total debt, we found extremely limited effects.