Liquidity Effects of Unemployment Insurance Benefit Extensions: Evidence from Consumer Credit Data*

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Abstract

Recipients of unemployment insurance benefits may allocate payouts towards consumption, savings, or servicing outstanding debt. This paper examines the effects that unemployment benefits have on mortgage, automobile loan, and credit card debt delinquency, exploiting the variation across states in the magnitude of unemployment benefit extensions that were provided in response to the Great Recession. We find that additional unemployment benefits reduced mortgage debt delinquency in locations that avoided large home price declines in the aftermath of the recession. Accordingly, we conclude that the stimulus effects of unemployment insurance may be muted to the extent that benefit payments are used to satsify housing debt obligations.

*The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System.

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1 Introduction

2 Empirical Strategy

We exploit cross-state variation in unemployment insurance (UI) benefit extensions. As we discuss in the next section, UI benefits vary at the state level and depend on states' labor market conditions. This feature of the policy poses a threat to identification, as labor market conditions have a direct effect on individuals' ability to borrow and pay down debt. Our identification strategy relies on policy discontinuities at the state border. More specifically, we assume that unlike policies that change discontinuously at the state border, the fundamentals that drive local economies such as supply and demand shocks, access to transportation, agglomeration benefits evolve continuously. To this end, we follow Holmes (1998), Card and Levine (2000), Dube et al. (2010) and Hagedorn et al. (2014) among many others, and use the border county design. We estimate the following specification:

$$y_{ipt} = \gamma_i + \tau_{pt} + \beta b_{it} + \varepsilon_{ipt}. \tag{1}$$

Here y_{ipt} denotes the outcome variable (for example, average delinquent debt per borrower) in period t of county i in border pair p. We allow counties to have different fixed effects, as captured by γ_i. We allow for a full set pair-time fixed effects, denoted by τ_{pt}, which capture the various changes in the economic environment that are common to the counties in the same pair. The term b_{it} denotes the (logarithm of the) weeks of UI benefits available in county i in period t. Note that b_{it} varies at the state level and is therefore the same for all counties in the same state. Finally, ε_{ipt} is a residual term that captures measurement error and additional county-specific factors that influence debt and delinquencies.

Our identification assumption of continuous fundamentals translates into the exogeneity of this error term to UI benefit policies. In other words, any supply or demand shocks that cause UI benefit durations to move differently in different states are similar across the border pairs and are captured by τ_{pt}.[1]

We estimate equation 1 using OLS and use a two-way cluster on state and border segment. Because UI benefit policy is set at the state level, we cluster standard errors on the state level. Further, since a single county can appear in more than one border pair, this mechanically induces a correlation across county pairs, and potentially along an entire border segment, which is accounted for by clustering standard errors on border segment. Additionally, observations are weighted by a county's population of persons 15 years or older in order to generalize results to the overall U.S. working-age population, noting the wide dispersion in county population sizes.

[1] While it is not possible to test the identification assumption directly, it is possible to test the implications of this assumption. One such implication is that differences in productivities between two neighboring states should not predict the difference in unemployment after controlling for UI benefits. Hagedorn et al. (2014) use this insight and find evidence consistent for the continuity of the fundamental drivers of local economies.

3 Data

We create a county-level dataset of debt, delinquencies, UI benefits, home prices, and foreclosure laws. The dataset is recorded at the quarterly frequency over the period of 2002:Q1 to 2012:Q4, capturing the run-up and aftermath of the Great Recession.

Debt and Delinquencies Our data on individual debt is derived from the FRBNY Consumer Credit Panel (CCP). CCP is a database that contains a longitudinal panel of individual debt histories, measured at the quarterly frequency since 1999:Q1. Credit and debt information are obtained from Equifax, which maintains credit histories for all U.S. residents that have ever applied for, taken out a loan or a credit card. Individuals are linked to a county based on the primary mailing address listed on their credit report. Because the CCP is derived from credit report data, the population that is represented in the CCP is the subset of people, mostly 18 or older, that have some credit history. We focus on three types of debt: (1) *first mortgage* debt, which refers to the primary loan that pays for a property at point of sale, which has priority over all other liens or claims on a property in the event of default, and is not necessarily the mortgage on a borrower's first home or primary residence; (2) *auto loans*, which are taken out to purchase a car, including automobile bank loans provided by banking institutions (banks, credit unions, and savings and loans associations) and automobile finance loans, provided by automobile dealers and financing companies; (3) and *bankcard* debt, which includes revolving accounts for banks, bankcard companies, national credit card companies, credit unions, and savings and loan associations.[2] The sampling procedure used to construct the CCP generates a five-percent random sample in each quarter that is representative of all individuals in the US who have a credit history and whose credit file includes the individual's social security number. See Lee and van der Klaauw (2010) for more details on the CCP. Our analysis focuses on how extensions of UI benefit durations affect delinquent debt on each type of credit. Delinquency is defined as being at least 30 days late on payment under our main definition, and at least 60 days late under an alternative definition. To this end, we consider three measures. We first investigate the effect of extensions on the amount of delinquent debt per borrower of a given credit type. To decompose the change in this measure into an extensive and an intensive margin, we also investigate how the delinquency rate and the amount of delinquent debt per delinquent person change with benefit extensions, respectively. One feature of the data deserves attention. It is quite common for individuals to have more than one line of a given type. This is particularly true for credit cards, where 70.1 percent of people that have a line of credit has at least two lines.[3] In this case, if someone is delinquent in any given line, we consider this individual as delinquent.

House Prices To study heterogeneous effects and to better understand the economic forces at play, we estimate how the effect of UI extensions varies for county pairs that have suffered large house price declines during the Great Recession relative the other pairs. To this end, we supplement our dataset with county-level house price data from the Federal Housing Finance Agency (FHFA). The FHFA provides a house price index (HPI) that reflects house price appreciation within a given county for the period 1975–2015. The HPI

[2] "Bankcard" and "credit card" are used interchangeably throughout this text.
[3] Figure is computed from 2012:Q4 data from FRBNY CCP.

is constructed using appraisal values and sales prices for mortgages bought or guaranteed by Fannie Mae and Freddie Mac.[4] Data is available for 1,116 of 1,172 of the county pairs over the 2002 to 2012 sample period.

State Foreclosure Laws The foreclosure process varies across states. Some states require judicial proceedings before a creditor can foreclose on a home that has been delinquent. Some states are nonjudicial, as they do not require such a process. A third category of states can be classified as a hybrid of the two systems. For the analysis in the paper, we group states into two – those always requiring judicial proceedings and those that do not. We use data from *RealtyTrac* to classify states into two groups.[5] The list of judicial and nonjudicial states are shown in Appendix Table B1. The judicial recourse classification allows one to test the hypothesis that unemployment insurance recipients are less likely to pay down their housing debts in states in which it is more difficult for the creditor to obtain recourse from debtors in default by virtue of judicial proceeding requirements.

Unemployment Insurance Benefits Our data construction of potential UI benefit durations follows that of Hagedorn et al. (2014). In normal times, unemployed workers in most states can receive UI benefits for up to 26 weeks. In the period that we study, there were two programs in place that caused variation over time. The Extended Benefits program (EB) allows for 13 or 20 weeks of extra benefits in states with elevated unemployment rates. The EB program is a joint state and federal program, whereby the federal government pays for half of the cost and determines a set of "trigger" criteria that, if met, allows states with sufficiently high insured and total unemployment rates to qualify. The second is the Emergency Unemployment Compensation program (EUC08). This program is federally funded and provides four tiers to states depending on labor market conditions. We use weekly trigger reports from the Department of Labor on which program has been triggered on, and construct the duration of extra weeks available. We aggregate the total duration of maximum weeks of benefits available to a quarterly frequency.[6]

Border Pairs Finally, as we discussed before, the identification strategy relies on the discontinuity of UI benefit policies at state borders. To do this, we supplement our dataset with the set of county pairs in Dube et al. (2010) that share a state border but belong to different states.[7] This yields a set of 1,134 U.S. counties that form 1,172 unique border county pairs along 107 border segments within all 49 contiguous U.S. states (including the District of Columbia), with many counties belonging to more than one pair. Because many counties lack sufficiently many individual records in the CCP to compute reliable delinquency measures, the data is subset so that the final working dataset has 775 counties that form 742 unique border county pairs along 96 border segments within all 49 states, with housing data available for 741 of the 742 county pairs. See Appendix C for details.

[4]The data are available online here. See Working Paper 16-01 by Bogin et al. (2016).

[5]See: `https://www.realtytrac.com/real-estate-guides/foreclosure-laws/`

[6]For more details on the EB and EUC programs, see Rothstein (2011).

[7]We remove six county pairs in the dataset that actually belong to the same state.

4 Results

4.1 Baseline

Table 1 reports our baseline estimates of UI effects on delinquent debt. Interestingly, we fail to find any effect of on mortgage, auto loan, and credit card debt. Table XX shows that this lack of any effect is robust to controlling for county-specific linear time trends. Changes in delinquent debt per borrower can happen along two margins. We denote changes in the share of the population that is delinquent as the extensive margin and changes in the delinquent amount owed per delinquent borrower as the intensive margin. Tables 2 and 3 investigate these extensive and intensive margin responses, respectively. Interestingly, both point to a null result on all of the three debt categories.

If credit cards were used to smooth consumption during unemployment, and if UI extensions provided a cheaper way than credit cards to smooth consumption, UI extensions would result in lower delinquencies for credit cards. Our results show that this is not the case. Our null finding for an effect of UI on credit card debt is consistent with Hundtofte et al. (2018), who find that credit demand appears to be procyclical, contrary to theories of consumption smoothing predicting countercyclical demand for credit. Further corroborating evidence comes from Braxton et al. (2018), who find that constrained job losers default and delever.

Table 1: Log - Delinquent Balances per Borrower

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) C.C.
Log - Benefit Weeks	0.0408	0.00947	-0.0408
	(0.107)	(0.0522)	(0.0865)
Observations	62,548	62,548	62,548
R-squared	0.972	0.956	0.935

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 or older.

Table 2: Log - Delinquent Shares

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) C.C.
Log - Benefit Weeks	0.0154	-2.12e-05	-0.0321
	(0.103)	(0.0293)	(0.0582)
Observations	62,548	62,548	62,548
R-squared	0.965	0.974	0.985

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 or older.

Table 3: Log - Delinquent Balances per Delinquent Borrower

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) C.C.
Log - Benefit Weeks	0.0254	0.00949	-0.00869
	(0.0266)	(0.0398)	(0.0372)
Observations	62,548	62,548	62,548
R-squared	0.980	0.857	0.952

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 or older.

4.2 Housing Bust

Prior research has established that UI extensions reduce delinquencies in mortgage debt among unemployed homeowners. What explains this discrepancy between our work and the existing literature? One possibility is the state of the housing market. The incentives to pay down mortgage debt in a time when house prices are depressed might be lower. In particular, if delinquencies and the resulting foreclosures are mostly driven by strategic considerations rather than liquidity constraints, one would expect lower house prices to be a factor preventing mortgage payments. To investigate this premise empirically, we split our sample into two based on the severity of the housing bust, and estimate UI effects on credit outcomes separately. To do so, we define a measure of the housing bust ΔH for a border county pair p as the average house price decline from the peak over the period $2005 - 2007$ to the trough post-2008, where the average is taken over the two counties in the pair p. More specifically,

$$\Delta H_p = \frac{1}{2} \sum_{j \in p} \frac{\max\limits_{t \in [2005,2007]} HPI_{jt} - \min\limits_{t \geq 2008} HPI_{jt}}{\max\limits_{t \in [2005,2007]} HPI_{jt}}, \tag{2}$$

where t indexes time (quarter) and HPI_{jt} denotes the level of the house price index in county j of pair p. We use county-level data to construct these measures and assign county pairs into "bust" pairs and "non-bust" pairs depending on whether ΔHP_p is above a certain threshold. To have equally-sized groups, we call a pair a "bust" pair if that pair experienced a housing bust larger than that of the median pair.

Indeed, our hypothesis is supported by the data. Table 4 shows that for housing non-bust county pairs, the effect of a 10 percent increase in UI benefits brings down first mortgage delinquent balances per borrower by approximately 2.5 percent, with strong statistical significance. This finding implies that as long as home prices maintain their values, mortgage holders receiving UI may use their benefits towards paying down their housing debts. The effect is economically significant: For our sample of observations, total delinquent mortgage debt per borrower in the U.S. was 10,993 dollars (in year 2012 real terms). In the absence of a sharp decline in home prices, a large increase in UI benefit durations, such as the one we have seen through the EB and EUC08 programs, can generate a substantial decline in mortgage debt, as individuals use some of the UI benefits to make mortgage payments. This result is consistent with Hsu et al. (2018) who find evidence using data from the Survey of Income and Program Participation (SIPP) that UI extentions reduce mortgage delinquencies and may act as housing market stabilizers. The difference in our study is that, in contrast to Hsu et al. (2018), we cannot measure the effect on the unemployed as we do not observe the employment status in our dataset. Instead, we measure the total effect in the county, including the potential response of employed individuals.

The first columns of Table 5 and Table 6 show that, within non-bust pairs, the decline in delinquent balances per mortgage borrower appears to be occurring on the extensive margin rather than the intensive margin, with the coefficient on *Log - Benefit Weeks (Non-bust)* being more negative and more statistically significant for mortgage-delinquent population shares, at -.205, than for mortgage-delinquent balances per delinquent borrower, at -.0478. Accordingly, the extensive margin accounts for approximately four-fifths of the overall effect on delinquent mortgage balances per borrower, conditioning on non-bust pairs.

Viewing the coefficient on *Log - Benefit Weeks (Bust)* in column (1) of 4, one sees that the liquidity effect of UI benefits in reducing mortgage debt delinquency is offset in counties that experienced a housing bust. Further, the difference between non-bust-pairs and bust-pairs in the effect of UI benefits on delinquent mortgage balances also appears to occur along the extensive margin, noting the difference between the coefficients within Table 5 being larger than the difference between the coefficients within Table 6. These results provide evidence that mortgage holders who lost their jobs in locations where housing prices suffered large losses, who may have otherwise chosen to use UI benefits to pay down their mortgage debt, may have chosen instead to allow their delinquent balances to accrue, as the value of the underlying collateral dropped relative to the amount of debt tied to the home.

When allowing the effect of UI benefits to vary between housing bust and non-bust county pairs, there does not appear to be a response in delinquent auto loan debt or delinquent credit card debt, just as in the baseline results.

Table 4: Log - Delinquent Balances per Borrower - Effect of Housing Bust

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) C.C.
Log - Benefit Weeks (Non-bust)	-0.252***	-0.0567	-0.0212
	(0.0762)	(0.0640)	(0.0674)
Log - Benefit Weeks (Bust)	0.151	0.0343	-0.0467
	(0.133)	(0.0681)	(0.116)
Observations	62,462	62,462	62,462
R-squared	0.972	0.956	0.935

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

Table 5: Log - Delinquent Shares - Effect of Housing Bust

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) C.C.
Log - Benefit Weeks (Non-bust)	-0.205***	-0.0397	-0.0447
	(0.0760)	(0.0557)	(0.0395)
Log - Benefit Weeks (Bust)	0.101	0.0151	-0.0266
	(0.133)	(0.0311)	(0.0776)
Observations	62,462	62,462	62,462
R-squared	0.966	0.974	0.985

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

Table 6: Log - Delinquent Balances per Delinquent Borrower - Effect of Housing Bust

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) C.C.
Log - Benefit Weeks (Non-bust)	-0.0478	-0.0170	0.0236
	(0.0400)	(0.0432)	(0.0480)
Log - Benefit Weeks (Bust)	0.0506*	0.0193	-0.0201
	(0.0295)	(0.0520)	(0.0480)
Observations	62,462	62,462	62,462
R-squared	0.981	0.857	0.952

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

4.3 Foreclosure Process: Judicial vs. non-Judicial

We examine if the results are sensitive to the foreclosure process. Some states require that a judicial proceeding occur prior to a bank seizing collateral in the case of default. Such requirements are costly to the lender in comparison to non-judicial proceedings that are available in other states. Consequently, we hypothesize that individuals residing in "non-judicial" states have larger incentive to stay out of mortgage default relative to individuals residing in "judicial" states, as the latter set of borrowers enjoy greater protections by way of higher repossession costs. Accordingly, we would predict that increased UI benefits would have a muted effect in reducing delinquent mortgage balances in states that offered judicial protections. Columns (1) and (3) of Table 7 somewhat support that prediction with positive coefficients estimated for the judicial interaction term, but the estimates are statistically insignificant. Allowing effects to vary contingent on being in a housing bust county pair in Table 8, we see somewhat stronger support for our prediction, with the upward pressure on delinquent balances per mortgage borrower due to judicial protections present in bust pairs but not in non-bust pairs. The coefficients for the judicial interaction terms in Table 8, however, are also statistically insignificant.

Table 7: First Mortgage: Response to Judicial Protections

VARIABLES	(1) Delinquent balances per borrower	(2) Delinquent balances per delinquent borrower	(3) Delinquent borrower share
Log - Benefit Weeks	0.0241	0.0210	0.00317
	(0.106)	(0.0291)	(0.103)
x Judicial	0.0380	0.0102	0.0278
	(0.0338)	(0.0142)	(0.0297)
Observations	62,548	62,548	62,548
R-squared	0.972	0.980	0.965

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Two-way clustered standard errors grouped by state and border segment.

Regressions include county FE and pair-year FE.

Regressions are weighted by population ages 15 years or older.

Dependent variables are expressed in natural-logarithms.

Table 8: First Mortgage: Response to Judicial Protections, with Housing Controls

VARIABLES	(1) Delinquent balances per borrower	(2) Delinquent balances per delinquent borrower	(3) Delinquent borrower share
Log - Benefit Weeks	-0.252***	-0.0463	-0.206**
	(0.0781)	(0.0410)	(0.0777)
x Bust Indicator	0.378**	0.0889*	0.289*
	(0.149)	(0.0529)	(0.156)
x Judicial	-0.00216	-0.00550	0.00335
	(0.0300)	(0.0137)	(0.0269)
x Judicial x Bust Indicator	0.0551	0.0220	0.0331
	(0.0414)	(0.0176)	(0.0357)
Observations	62,462	62,462	62,462
R-squared	0.972	0.981	0.966

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.
Dependent variables are expressed in natural-logarithms.

5 Robustness of Results

5.1 Delinquency length: 60 days or more

The main results identify an individual as a delinquent borrower for a particular type of debt if that person has balances that are over 30 days past due and over $200 for that type of debt. This section modifies that definition to include are only 60 days past due or more, keeping the $200 threshold. As per Tables 9, 10, and 11, there appears to be no effect of UI benefits on delinquent mortgage, auto loan, or credit card debt, absent allowing for heterogeneous effects. The null finding here is consistent with Section 4.1.

When allowing for the effect of UI benefits to be dependent on the occurrence of a housing bust, the results in this section show that there is indeed a liquidity effect of UI benefits in reducing delinquent mortgage debt, conditional on home prices not experiencing steep declines. The effect is offset, however, in counties that experienced a housing bust, just as in Section 4.2. The magnitudes of the heterogeneous effects of UI benefits on mortgage delinquency indeed appear to be stronger when defining delinquency by a 60-day threshold rather than a 30 day threshold. The amplification in the estimates suggests that while UI benefits may prevent households who hold good collateral from entering serious delinquency, UI benefits may actually incentivize households who hold bad collateral to become delinquent, as the households are more willing to part from the underlying asset and can maintain their consumption from UI benefits rather than from finding new employment.

Table 9: Log - Delinquent Balances per Borrower, Delinquent 60 days

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks	0.0691	0.00804	-0.0396
	(0.151)	(0.0609)	(0.0922)
Observations	62,548	62,548	62,548
R-squared	0.965	0.958	0.937

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Two-way clustered standard errors grouped by state and border segment.

Regressions include county FE and pair-year FE.

Regressions are weighted by population ages 15 years or older.

Table 10: Log - Delinquent Shares, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks	0.0475	9.04e-05	-0.0328
	(0.148)	(0.0348)	(0.0631)
Observations	62,548	62,548	62,548
R-squared	0.963	0.974	0.984

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

Table 11: Log - Delinquent Balances per Delinquent Borrower, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks	0.0216	0.00795	-0.00684
	(0.0333)	(0.0485)	(0.0387)
Observations	62,548	62,548	62,548
R-squared	0.960	0.821	0.954

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

Table 12: Log - Delinquent Balances per Borrower, Housing Bust Effect, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.353***	-0.0508	-0.0220
	(0.102)	(0.0779)	(0.0754)
Log - Benefit Weeks (Bust)	0.228	0.0304	-0.0447
	(0.187)	(0.0767)	(0.123)
Observations	62,462	62,462	62,462
R-squared	0.965	0.958	0.937

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

Table 13: Log - Delinquent Shares, Housing Bust Effect, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.259**	-0.0398	-0.0461
	(0.107)	(0.0736)	(0.0468)
Log - Benefit Weeks (Bust)	0.166	0.0155	-0.0270
	(0.192)	(0.0327)	(0.0836)
Observations	62,462	62,462	62,462
R-squared	0.963	0.974	0.984

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

Table 14: Log - Delinquent Balances per Delinquent Borrower, Housing Bust Effect, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.0944	-0.0110	0.0241
	(0.0581)	(0.0413)	(0.0524)
Log - Benefit Weeks (Bust)	0.0618*	0.0149	-0.0178
	(0.0347)	(0.0645)	(0.0492)
Observations	62,462	62,462	62,462
R-squared	0.960	0.821	0.954

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE and pair-year FE.
Regressions are weighted by population ages 15 years or older.

5.2 Heterogeneous Trends

As another model robustness check, we add the term $\eta_i \times t$ to the right-hand side of equation 1, allowing for heterogeneous linear time trends. As per the tables below, the finding is maintained that increased UI benefits have a heterogeneous effect on housing debt delinquency depending on whether a county experiences a housing bust, but with less statistical precision and with muted magnitudes. Non-bust counties experience a slight reduction in delinquent mortgage balances as UI benefits increase, while bust counties experience a slight increase in delinquent mortgage balances. Also, just as the magnitudes of the heterogeneous effects of UI benefits were larger when defining delinquency by a 60-day threshold than by a 30-day threshold in the absence of county-specific time trends, so too with the inclusion of those time trends. The relatively stronger effects observed for more serious cases of delinquencies supports the hypothesis that households are strategic in choosing whether to allocate UI benefits to mortgage debt service depending on the price movements of the underlying collateral.

As in prior sections, there appears to be limited evidence of an effect of UI benefits on auto loan or credit card debt.

Table 15: Log - Delinquent Balances per Borrower - Het. Trends, Delinquent 30 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.0400	-0.0110	0.0270
	(0.0895)	(0.0546)	(0.0445)
Log - Benefit Weeks (Bust)	0.0734	0.00984	0.0126
	(0.0775)	(0.0296)	(0.0514)
Observations	62,462	62,462	62,462
R-squared	0.979	0.963	0.959

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE, pair-year FE, and county-specific trends.
Regressions are weighted by population ages 15 years or older.

Table 16: Log - Delinquent Shares - Het. Trends, Delinquent 30 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.0270	-0.0354	-0.0285
	(0.0746)	(0.0361)	(0.0259)
Log - Benefit Weeks (Bust)	0.0440	0.00943	-0.0224
	(0.0757)	(0.0244)	(0.0243)
Observations	62,462	62,462	62,462
R-squared	0.975	0.980	0.992

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE, pair-year FE, and county-specific trends.
Regressions are weighted by population ages 15 years or older.

Table 17: Log - Delinquent Balances per Delinquent Borrower - Het. Trends, Delinquent 30 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.0130	0.0245	0.0554
	(0.0327)	(0.0344)	(0.0373)
Log - Benefit Weeks (Bust)	0.0294	0.000410	0.0349
	(0.0210)	(0.0313)	(0.0367)
Observations	62,462	62,462	62,462
R-squared	0.984	0.879	0.965

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE, pair-year FE, and county-specific trends.
Regressions are weighted by population ages 15 years or older.

Table 18: Log - Delinquent Balances per Borrower - Het. Trends, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.0826	0.0332	0.0483
	(0.106)	(0.0595)	(0.0467)
Log - Benefit Weeks (Bust)	0.106	0.00760	0.0205
	(0.107)	(0.0379)	(0.0541)
Observations	62,462	62,462	62,462
R-squared	0.973	0.966	0.962

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE, pair-year FE, and county-specific trends.
Regressions are weighted by population ages 15 years or older.

Table 19: Log - Delinquent Shares - Het. Trends, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.0373	-0.0243	-0.0247
	(0.0861)	(0.0456)	(0.0271)
Log - Benefit Weeks (Bust)	0.0731	0.0123	-0.0183
	(0.108)	(0.0309)	(0.0268)
Observations	62,462	62,462	62,462
R-squared	0.973	0.981	0.992

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE, pair-year FE, and county-specific trends.
Regressions are weighted by population ages 15 years or older.

Table 20: Log - Delinquent Balances per Delinquent Borrower - Het. Trends, Delinquent 60 days+

VARIABLES	(1) First Mortgage	(2) Auto Loan	(3) Credit Card
Log - Benefit Weeks (Non-bust)	-0.0454	0.0575	0.0730*
	(0.0520)	(0.0353)	(0.0407)
Log - Benefit Weeks (Bust)	0.0331	-0.00468	0.0388
	(0.0305)	(0.0322)	(0.0375)
Observations	62,462	62,462	62,462
R-squared	0.965	0.851	0.967

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Two-way clustered standard errors grouped by state and border segment.
Regressions include county FE, pair-year FE, and county-specific trends.
Regressions are weighted by population ages 15 years or older.

6 Conclusion

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A Summary Statistics

Dollar figures are inflated to 2012 values by the Consumer Price Index, produced by the Bureau of Statistics.

Table A1: Delinquent Balances per Borrower (2012 $) - 30 days or more

	mean	p10	p25	p50	p75	p90	count
Mortgage	7,029.95	2,549.37	3,708.56	5,420.04	8,242.57	12,889.76	62,548
Auto	907.81	455.01	609.42	819.91	1,111.80	1,460.65	62,548
Credit Card	635.90	387.25	491.23	613.24	750.98	903.12	62,548

Table A2: Delinquent Shares - 30 days or more

	mean	p10	p25	p50	p75	p90	count
Mortgage	0.06	0.03	0.04	0.05	0.07	0.09	62,548
Auto	0.09	0.05	0.06	0.08	0.11	0.14	62,548
Credit Card	0.13	0.08	0.09	0.12	0.15	0.19	62,548

Table A3: Delinquent Balances per Delinquent Borrower (2012 $) - 30 days or more

	mean	p10	p25	p50	p75	p90	count
Mortgage	121,287.85	63,851.46	79,725.83	102,867.80	140,325.28	205,233.38	62,548
Auto	10,250.13	7,600.97	8,704.82	10,013.31	11,491.42	13,009.28	62,548
Credit Card	5,306.86	3,580.74	4,190.25	4,964.87	6,002.57	7,350.47	62,548

Table A4: Delinquent Balances per Borrower (2012 $) - 60 days or more

	mean	p10	p25	p50	p75	p90	count
Mortgage	4,436.83	1,041.91	1,734.81	2,909.88	5,201.23	9,153.18	62,548
Auto	549.31	229.60	331.75	480.24	685.25	943.00	62,548
Credit Card	563.02	335.72	429.54	539.34	669.42	811.29	62,548

Table A5: Delinquent Shares - 60 days or more

	mean	p10	p25	p50	p75	p90	count
Mortgage	0.03	0.01	0.02	0.03	0.04	0.06	62,548
Auto	0.06	0.03	0.04	0.06	0.08	0.11	62,548
Credit Card	0.11	0.07	0.08	0.11	0.14	0.17	62,548

Table A6: Delinquent Balances per Delinquent Borrower (2012 $) - 60 days or more

	mean	p10	p25	p50	p75	p90	count
Mortgage	123,749.11	58,823.71	78,396.52	104,727.63	146,301.31	214,690.83	62,548
Auto	8,693.79	6,312.64	7,331.74	8,440.31	9,700.88	11,083.03	62,548
Credit Card	5,219.73	3,453.06	4,050.75	4,848.08	5,944.72	7,367.22	62,548

Table A7: Weeks of Unemployment Insurance, Before and After Recession

	mean	min	p25	p50	p75	max	count
2002-2007	30	26	26	26	39	71	33,164
2008-2012	72	26	56	75	93	99	29,384

Table A8: County Pair Bust Size

	mean	p10	p25	p50	p75	p90	count
Bust Size (p.p.)	14.10	2.02	5.80	12.74	20.77	27.30	741

B Foreclosure Laws

Table B1: State Foreclosure Laws

Judicial	*Non-Judicial*
Connecticut	Alabama
Delaware	Alaska
Florida	Arizona
Illinois	Arkansas
Indiana	California
Kansas	Colorado
Kentucky	District of Columbia
Louisiana	Georgia
Maine	Hawaii
Maryland	Iowa
Massachusetts	Michigan
Nebraska	Minnesota
New Jersey	Mississippi
New Mexico	Missouri
New York	Montana
North Dakota	Nevada
Ohio	New Hampshire
Oklahoma*	North Carolina
Pennsylvania	Oregon
South Carolina	Rhode Island
South Dakota*	Tennessee
Vermont	Texas
Wisconsin*	Utah
	Virginia
	Washington
	West Virginia
	Wyoming

* Oklahoma, South Dakota, and Wisconsin have non-judicial foreclosure provisions in their state laws; however, judicial foreclosure is common.

C Sample Selection

We restrict our sample to counties for which there is sufficiently many observations in order to compute reliable delinquency measures. Data is featured at the quarterly frequency from 2002:Q1 to 2012:Q4. Prior to removing observations, the dataset of counties within county pairs consists of 1,134 counties, 1,172 distinct county pairs, 107 border segments, and 49 states, forming 103,136 observations.

First, we drop all observations of counties that have fewer than fifty individual records for first mortgage, auto loan, or credit card debt at any point in time in the sample period, as well as any associated pair-county observations. In this first step, the data is reduced to 775 counties, 742 distinct county pairs, 96 border segments, and 49 states, forming 65,296 observations.

Second, we drop observations for which any outcome variable, namely delinquent balances per borrower, delinquent balances per delinquent borrower (in levels) is missing, as well as any associated pair-county observations, reducing the dataset to 62,548. In the second step, the counts for counties, distinct county pairs, border segments and states are preserved at 775, 742, 96, and 49, respectively.

Third, we check to see if any of the outcome variables are recorded at zero for any observation, noting that the natural logarithm of zero is undefined. We find that once the data is reduced to the 62,548 observations described in the second step above, none of the outcome variables are recorded at zero for any observation, leaving us with the final dataset.

Among the 742 distinct county pairs in the final dataset, 741 county pairs have housing data available, resulting in a slightly smaller dataset of 62,462 observations when UI benefits are interacted with the constructed housing bust measure.