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Abstract

Texas is the only US state that limits home equity borrowing to 80 percent of home value. This paper exploits this policy discontinuity around the Texas' interstate borders and uses a multidimensional regression discontinuity design framework to find that limits on home equity borrowing in Texas lowered the likelihood of mortgage default by about 1.5 percentage points for all mortgages and 4-5 percentage points for nonprime mortgages. Estimated nonprime mortgage default hazards within 25 to 100 miles on either side of the Texas' border are about 20 percent smaller when crossing into Texas.

Keywords: Home Equity, Mortgage Default, Negative Equity
JEL Numbers: G21, G28, R28

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1. Introduction

The subprime mortgage crisis played a central role in the onset of the Great Recession that led to record post-war joblessness and long-term unemployment. As house prices plunged, home equity declined sharply and many homeowners went underwater on their mortgages; their negative equity positions leaving them owing lenders more than their homes were worth. Apart from large swings in house prices, excessive borrowing during the housing boom—through cash-out refinancing, closed-end home equity loans/second mortgages, and Home Equity Lines of Credit (HELOC)—was a key factor in the rising incidence of negative equity and subsequent default. Mian and Sufi (2011) found that about 40 percent of new mortgage defaults during the housing crisis were driven by active home equity extraction. Using a sample of homeowners from California, Laufer (2011) notes that even after a precipitous decline in house prices during the bust, a vast majority of homeowners who defaulted would still have had positive equity had they not engaged in aggressive home equity extraction during the boom.

Given the role of excessive borrowing in precipitating the housing crisis, economists and policymakers have focused significant attention on effective regulations to curb unaffordable mortgage debt. But evidence whether such regulations indeed work remains thin; laws limiting active home equity extraction in the US are rare. Texas is the only state that explicitly limits borrowing against home equity.[1] A 1997 constitutional amendment in Texas (henceforth, also referred to as "*the Texas policy*") allowed home equity loans and cash-out refinancing, but restricted overall borrowing against housing equity to 80 percent or less of home value. That is, the combined loan-to-value (LTV) ratio of any pre-existing notes along with the new loan—home-equity loan, cash-out refinancing or HELOC—cannot exceed 80 percent in Texas.

Despite the policy's unique nature and potential implications, no paper has empirically estimated its impact on overall leverage and mortgage defaults.[2] This paper fills this void and makes two contributions to the previous literature on the impact of home equity extraction on mortgage default. First, to the best of my knowledge, this is the first paper to empirically estimate the impact of Texas' home equity restrictions on mortgage default. Second, the paper exploits the policy discontinuity around the Texas border to identify the causal effect of home equity extraction on

[1] Regulations to limit initial mortgage debt used to purchase a home have long existed in countries such as Austria, Poland, China and Hong Kong.
[2] Laufer (2011) used a property level dataset from California and simulated the impact of Texas' home equity withdrawal restrictions on default rates, but did not directly estimate the impact of Texas' restrictions.

mortgage default in a Regression Discontinuity Design (RD) framework.[3] The empirical strategy is to compare mortgage default probabilities or hazard rates of otherwise similar individuals or loans located in proximate counties on either side of the Texas border, controlling for smooth functions of geographical location. In doing so, the paper helps disentangle the role of active home equity extraction from other factors such as house price declines and liquidity constraints as contributors to the subprime default crisis.[4]

In addition to estimating the traditional one-dimensional RD specifications in distance to the Texas border, following Dell (2010), I employ a multidimensional RD approach and model the Texas border with neighboring states as a multidimensional discontinuity in latitude and longitude space. Because a suitably flexible multidimensional RD polynomial can be high-dimensional, I use a data-driven Least Absolute Shrinkage and Selection Operator (LASSO) approach to select the number of terms Tibshirani (1996) . A methodological contribution of the paper is to combine the multidimensional RD setup with recently proposed post-double-LASSO treatment effect estimator from Belloni et al. (2014a) to estimate the causal effect of the Texas policy on mortgage default in a semiparametric partially linear framework.

Using two large databases—(1) all residential mortgages from Loan Performance and (2) nonprime mortgages from CoreLogic—the paper has three primary findings. First, Texas' home equity restrictions had a significantly negative impact on the probability of mortgage default close to the Texas border. The RD estimates for all residential mortgages indicate that the Texas policy lowered mortgage default probability by about 1.5 percentage points between 2007 and 2011—a significant effect considering that the share of individuals defaulting in the data is just about 4.3 percent on average from 2007 to 2011.

Second, the policy had an even larger impact on nonprime mortgage borrowers—a group on which the Texas borrowing restrictions were likely most binding—and significantly lowered their

[3] Also known as boundary or border discontinuity design (BDD), the method followed in the paper is a version of the widely used RD framework applied to geographic or spatial discontinuity. See Black (1999) for an early exposition of this methodology and (Bayer et al., 2007; Dell, 2010; Dhar and Ross, 2012) , among others, for a recent applications. (Pence, 2006) applies it to estimate the impact state laws on mortgage credit. Because there is no time variation in the Texas policy to cap borrowing against home equity, a standard difference-in-difference framework cannot be applied.

[4] Since the regulation affected mortgage defaults primarily through its impact on negative home equity, the paper contributes to the reduced form evidence on the causal link between negative equity on mortgage default. Directly estimating the impact of negative home equity on mortgage default is difficult as unobserved taste for mortgage debt may be correlated with underlying preferences to walk away from one's mortgage. Also, most datasets do not have precise measures of negative equity. See Bhutta et al. (2010) for an in-depth analysis of the impact of negative equity on default.

mortgage default rate by about 4-5 percentage points. This is consistent with previous evidence that while negative equity is necessary to push homeowners over the edge and default, it shares a strong interaction with credit constraints in affecting default; those with negative equity who also face binding credit constraints are more likely to default (Campbell and Cocco, 2011; Elul et al., 2010).

Third, using loan-level data on nonprime borrowers, the paper finds evidence of a large discontinuity in mortgage default hazards at the Texas border with neighboring states. Estimated default hazards for mortgages within 25 to 100 miles of the Texas' border decline by about 20 percent on the Texas side. Overall, the paper finds evidence that the Texas policy negatively affects mortgage default—a finding that is robust to placebo tests and to use of aggregate state/county level data as well as detailed loan-level data.

These findings are consistent with theory, as there are strong *a priori* reasons why Texas home equity restrictions may discourage default. First, the policy likely boosted home equity by capping current LTV to 80 percent and, thereby, reduced the incidence of negative equity. Economic theory predicts a strong causal link between lack of home equity and mortgage default. In option-theoretic models, negative equity (i.e., current combined LTV$\geq 100\%$) is a necessary condition for triggering default; the homeowner defaults if the market value of the mortgage exceeds the home value plus any associated costs of walking away from a home e.g., moving costs (Deng et al., 2000; Vandell and Thibodeau, 1985).[5] Second, homeowners are more likely to engage in collateralized borrowing through home equity extraction to finance current consumption—those with liquidity constraints and homeowners lacking self-control or financial sophistication—are also the type of borrowers more likely to default on their mortgages. Moreover, they leave themselves with less margin for error should they encounter an economic setback.[6] Third, by limiting the overall mortgage burden to 80 percent of home value, the Texas law affected current overall LTV as well as the total mortgage payment, thereby reducing the probability of negative equity and improving

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[5] See Kau and Keenan (1995) and Quercia and Stegman (1992) for a comprehensive review of the literature. Default may not take place as soon as the household enters a negative equity position. There could be transaction costs to defaulting. Also, the option is permanently lost once exercised and therefore the household may choose to wait and pick a period that maximizes the option value of default, which typically will increase if house price declines further. Moreover, the household may not default instantly and wait if house prices are expected to recover in future.

[6] Homeowners without liquidity constraints will have little reason to borrow against housing wealth to finance current consumption during a housing boom, as rising house prices simply mean a higher cost of using their house without any real wealth effects (Campbell and Cocco, 2007; Cooper, 2013; Sinai and Souleles, 2005). For the impact of house prices on consumption, see (Duca et al., 2010; Engelhardt, 1996a). For the role of liquidity constraints see (Hurst and Stafford, 2004); for self-control on indebtedness, see (Gathergood, 2012; Laibson, 1997). For the role of financial sophistication on debt or/and default see (Agarwal et al., 2009, 2010; Duca and Kumar, 2014; Gerardi et al., 2010), among others.

mortgage affordability Campbell and Dietrich (1983). And finally, previous research has found a positive link between credit quality deterioration and home equity line utilization (Agarwal et al. (2006), with the implication that the Texas policy may have discouraged homeowners from cashing out their home equity lines in anticipation of a credit shock, thus boosting home equity relative to other states and curbing eventual default.

Due to the policy's strong implications for mortgage default avoidance, the popular press and others have extensively examined why it may be an important factor that can explain how Texas navigated the housing crisis without the surge in defaults witnessed elsewhere in the nation (Katz, 2010; Norris, 2012). Such anecdotal evidence is largely based on Texas-US comparisons similar to Figure 1, which, using data from the Mortgage Bankers Association (MBA), shows that Texas had a lower incidence of subprime serious delinquencies not only compared with the nation but also relative to the neighboring states. Moreover, the post-2007 gap widened as the mortgage crisis deepened with the onset of the Great Recession.[7]

Nonetheless, despite strong theoretical support for the belief that the Texas policy lowered defaults, simple comparisons between Texas and other states could conflate the impact of home equity restrictions with differences in other state level policies and characteristics. Moreover, the precise effect remains uncertain for a variety of reasons. First, by not allowing full access to housing wealth, the restriction may have tightened liquidity constraints on homeowners and, therefore, some homeowners on the margin would be more likely to default Laufer (2011). Second, the restriction capped combined current LTV but left initial LTV unrestricted, and therefore homebuyers may be tempted to make lower initial down payments, knowing that future borrowing against home equity will be restricted. Third, some homeowners may be driven to other more expensive sources of debt, e.g., credit card debt and payday loans. Higher credit card utilization will further tighten credit constraints on borrowers, making them more likely to default. Fourth, since negative equity is just a necessary and not a sufficient condition to default, not all households that go underwater end up defaulting on their mortgages Foote et al. (2008). And finally, the restriction negatively affected issuance of second-lien closed-end home equity loans or HELOCs, the type of loans likely to be

[7] Going beyond simple comparisons of mortgage default rates, Table A1 in Appendix A controls for differences in other characteristics between Texas and rest of the U.S. and shows that prime delinquency rates in Texas were about 1 percentage point lower and subprime delinquency about 3 percentage points lower than in the rest of US. The estimates in all columns of Table A1 remain robust to restricting the sample to Texas' neighboring states.

current longer, relative to first liens Jagtiani and Lang (2010).[8] Therefore, the actual quantitative impact of Texas' home equity restrictions on mortgage default remains an important empirical puzzle that this paper helps resolve. An important limitation is the paper's inability to separately identify the economic significance of the multiple channels through which the policy affected mortgage default. Nevertheless, the paper's central finding that the Texas policy inhibits mortgage default has important implications for the effectiveness of potential rules aimed at curbing excessive mortgage debt and default.[9]

The remainder of the paper proceeds as follows. Section 2 presents a brief description of the Texas' home equity restrictions. Section 3 describes the data and presents summary statistics. Section 4 presents the econometric specification and results. Robustness and placebo tests are presented in Section 5. Finally, there is a brief conclusion.

2. Texas Home Equity Restrictions

Texas has historically maintained strong homestead protection laws to shield homeowners against forced sale and seizure. See Kumar and Skelton (2013) for a chronology of major events in the evolution of homestead protection laws in Texas. As part of a longstanding effort to keep creditors at bay, homeowners in Texas were severely restricted from borrowing against even their own housing wealth. Of course, homebuyers could get a mortgage loan to finance the home purchase. But once the home was purchased, home equity extraction was severely limited. Other than home purchase, the Texas constitution of 1876 permitted only two other types of liens on homestead: (1) home improvements and (2) taxes (Graham, 2007). Since 1995, in the event of divorce, jointly owned homes could be converted to full ownership through a home equity loan to pay off the joint-owner's share of home equity. Barring these exceptions, however, almost all other forms of home equity borrowing remained out of bounds for Texas' homeowners. In particular, cash-out refinancing, a widely used form of home equity withdrawal in the rest of US, was not allowed. While refinancing, home equity could be used only to defray the cost of refinancing. Home equity loans through second mortgages or home equity line of credit also were prohibited.

[8] In addition, HELOCs are used by relatively higher credit borrowers and by lowering HELOC, the restriction may have led to a shift in mortgage debt distribution in favor of first liens (Lee et al., 2012).

[9] Consumer Finance Protection Bureau (CFPB) has issued new mortgage rules, amending Regulation Z that implements the Truth in Lending Act (TILA), significantly tightening underwriting standards for all new qualified mortgages. No-doc loans, interest-only mortgages, and negative amortization mortgages have been excluded from the qualified mortgage list. Mortgages lenders must now make a reasonable, good-faith determination of a borrower's ability-to-repay a closed-end mortgage loan, before extending credit. Underwriting criteria require that borrower's back-end loan-to-income ratio should not exceed 43 percent.

Subsequent to passage of Proposition 8 by Texas voters, House Joint Resolution 31 amended Section 50, Article XVI of the Texas constitution in 1997 and allowed home equity loans through second mortgages or cash-out refinancing. Total borrowing against home equity was, however, capped to no more than 80 percent of the home's appraised value; no such restrictions were placed on a first mortgage while purchasing the home.[10] There is a widespread belief that this restriction severely limited a Texas homeowner's ability to obtain home equity-related credit during the housing boom from 2000 to 2006 and contributed to a lower incidence of negative equity than elsewhere in the nation when the housing market collapsed and mortgage defaults spiked higher.

3. Data and summary statistics

Data on Mortgage default and other mortgage characteristics

All analysis in the paper is based on two large loan-level databases of residential mortgages. First, the database of residential mortgages from Lender Processing Services (LPS)—henceforth referred to as LPS data—contains monthly information on 130 million installment-type mortgage loans covering about two-thirds of the residential mortgage market in the US from 1992 to the present. Second, I use a database of 20 million loans covering all non-agency private label securitized nonprime (subprime and Alt-A) mortgages in the US available from CoreLogic Loan Performance—henceforth referred to as ABS data— from 1992 to the present.[11] Both of these databases are obtained from Risk Assessment, Data Analysis, and Research (RADAR) data warehouse—a centralized database of consumer credit and related securities for the Federal Reserve System. Both LPS and ABS databases contain information on monthly delinquency status through the life of the loan since origination and other key static and dynamic mortgage characteristics. They also have information on the location of property securing each mortgage: the property's state, Zip Code, and county.

I use the entire LPS (for all mortgages) and ABS database (for nonprime mortgages) to calculate annual county-level averages of mortgage default rate and other mortgage characteristics.

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[10] In addition to the cap on the home equity lending Texas also has other provisions to curb predatory lending as summarized in Graham (2007). Only authorized lenders can make home equity loans. The mortgage lien must have the consent of both the owner and spouse. Home equity loans must be closed only at the office of the lender, attorney or the title company. Fees for home equity loans may not exceed 3 percent of principal amount. The Texas law allows only one home equity loan at a time and in case of refinancing, only one refinancing per year. Lenders must provide a 12-day notice before home equity closing. The borrower or spouse has the right to rescind the loan within three days after loan closing. The 1997 constitutional amendment also prohibited home equity loans with balloon payments, negative amortization, pre-payment penalties. Further, HELOCS were not allowed until 2003.

[11] See Chomsisengphet and Pennington-Cross (2006) for a detailed analysis of this data in a different context, Haughwout and Okah (2009) for negative equity calculations, and Bajari et al. (2008) for subprime mortgage default.

A mortgage is considered in default if it is 90 or more days delinquent, in foreclosure, or Real Estate Owned (REO). Other mortgages characteristic averaged at the county-level and used as baseline covariates are: original FICO score; share of mortgages with initial LTV greater than 80 percent; share of adjustable rate mortgages; and share of mortgages used for cash-out refinancing.[12] All RD results of county-level mortgage default rates are based on mortgages in Texas and the four neighboring states— Arkansas, Louisiana, New Mexico and Oklahoma from 2007 to 2011.

In addition to county-level mortgage default rate models, the paper also estimates hazard models of mortgage default using the entire monthly delinquency history of nonprime mortgages until November 2013. Mortgage default hazard models are based on a 30% random sample of all nonprime loans from the ABS database originating from 1998 to 2006 secured against properties in Texas and the four neighboring states.

County-level house price growth

County-level house prices are based on CoreLogic quarterly house price index data. A drawback of using CoreLogic county-level house price data is that availability varies by county size and they are not available for many smaller counties. To circumvent this problem, I impute the quarterly change in house prices for missing counties using the average quarterly house price change of non-missing adjacent counties, wherever possible, to construct a more complete county-level house price change data. Data on distance between counties is from (Collard-Wexler, 2014).[13]

County-level unemployment rate, median household income and lending standards

Data on the county unemployment rate and median household income are from BLS Local Area Unemployment Statistics (LAUS) and the Census Bureau's US counties database, respectively. Following Dell'Ariccia et al. (2012), to control for differences in lending standards, I use data from the Urban Institute on county-level mortgage denial rates calculated based on HMDA data.

State-level covariates

In robustness checks I also account for cross-state differences in institutions and legal arrangements (such as foreclosure rules) using state-level data presented in Pence (2006), Ghent and

[12] While the LPS data has information on just the initial LTV of each mortgage (i.e. loan amount of each mortgage in the database as a share of the purchase price of the property securing that mortgage), the ABS database on nonprime mortgages contains information on combined initial LTV (CLTV) (i.e. combined loan amount of all mortgages as a share of the purchase price of the property securing each mortgage in the database).

[13] To check the sensitivity of our results to use of imputed house prices for smaller counties, I estimated all econometric specifications in the paper using (1) actual data available for larger counties and (2) the FHFA state level house price index instead of county level house prices and found that estimated effects were qualitatively and quantitatively similar.

Kudlyak (2011), Vicente (2013) , and Choi (2012).[14] To test the validity of the main identification assumption that homeowners do not precisely manipulate their location around the Texas border, I use state-to-state migration calculations from taxfoundation.org based on tax return data from the IRS Statistics of Income (SOI) division.

Data on geographic location (latitude, longitude) and distance

In the traditional one-dimensional RD set up, the minimum distance of the counties' centroid to the Texas interstate border serves as the forcing variable. Data on the minimum distance is from state border dataset of Holmes (1998). Each county is assigned to 25-, 50-, 75-, or 100-mile bands around the Texas' border with neighboring states based on the minimum distance between the Texas border and the county's centroid. For loan-level mortgage default hazard models, each loan is assigned to one of these distance bands based on the property's county. Figure 2 shows the counties in various distance bands around the border. Census geocode data is used to get information on latitude and longitude of county centroids for constructing the multidimensional RD polynomial (Crow, 2013; Pisati, 2001).

Summary statistics and simple mean comparisons

The summary statistics in Table 1 can be used to get a first cut estimate of the discontinuity in the outcome variable—mortgage default rates—across the Texas border. The default rate for all mortgages on the Texas side of the 25-mile band around the interstate border averaged about 4 percent between 2007 to 2011 (Column 1), 1 percentage point lower than in the neighboring states (Column 2). While the difference is statistically insignificant within 25 miles, it grows to 1.4 percent and turns significant when the band is expanded to 50 miles around the Texas border. Nonprime mortgage default rates, on the other hand, averaged about 11 percent between 2007 and 2011 on the Texas side of the 25-mile band—4 percentage points lower than neighboring states and statistically significant at 10 percent level. The 4 percentage point difference is significant at 5 percent level when the band is expanded to 50 miles. Other covariates are generally balanced between Texas and the bordering states within 25 miles, except for a significantly lower incidence of cash-out refinance mortgages and adjustable rate mortgages in Texas and a significantly higher unemployment rate.

The large and statistically significant difference in the share of cash-out refinance mortgages is tentative evidence in support of the view that the Texas policy successfully limited the ability of

[14] To account for state-level differences in policy affecting housing supply, in robustness checks, I also control for state level housing supply elasticity from Saiz (2010).

borrowers to extract home equity through cash-out refinancing. A higher unemployment rate in Texas suggests that mortgage default rates would have been even lower in Texas, had joblessness been the same as the neighboring states. Differences in means between Texas and neighboring states emerge in some covariates when the sample is expanded to 50 miles. Nevertheless, RD evidence (presented later in the paper) indicates that almost all baseline covariates, except for the unemployment rate, evolve continuously at the discontinuity threshold.

4. Econometric Specification and Results

4.1 Traditional RD Specification based on grouped county level data

Since the geographic location measures vary only at the county level, I start by estimating simple county-level regressions of mortgage default rate on the RD polynomial and other baseline covariates grouped to county and year level from 2007-2011. All county-level estimates are weighted by number of mortgages and standard errors clustered at the county level to account for potential serial correlation.[15] The baseline RD specification can be written as:

$$PctMortDefault_{cst} = \beta_0 + \beta_1 Texas_s + \delta g(MinDist_{cs}) + \gamma Z_{cst} + d_t + u_{cst} \qquad (1)$$

In equation (1), c denotes county, s indexes state and t denotes year. $PctMortDefault_{cst}$ is county-level share of mortgages that are 90 days or more delinquent, in foreclosure or REO. The treatment variable $Texas_s$ is a dummy for mortgages located in Texas. $g(MinDist_{cs})$ is the RD polynomial in minimum distance of the county's centroid to the Texas border (normalized to zero at the border). Z_{cst} is a set of other exogenous county-level covariates correlated with the mortgage default rate. d_t is a time effect. The error term u_{cst} represents unobserved county-level taste or preference for mortgage default.

For a consistent estimate of the policy impact, β_1, the key identifying assumption is that, while the treatment variable $Texas_s$ is a discontinuous function of $MinDist_{cs}$, all other unobserved factors vary continuously with location and $E(u_{cst}|MinDist_{cs}, Z_{cst}) = 0$.[16] Intuitively, the necessary condition for identification is that homeowners in counties on the Texas side of the border are not

[15] Such an approach for RD applications where key variables vary at a group level, has been suggested in (Card and Shore-Sheppard, 2004). Since much of the variation in covariates is only at the county and time level, estimates from regression on grouped county-year level data weighted by number of mortgages in each county would be very close to estimates obtained from all loans (Angrist and Pischke, 2008). Estimates using loan-level data were qualitatively indistinguishable and are available on request from the author.

[16] Equivalently, expected potential mortgage default outcomes for Texans (Non-Texans) are a smooth function of distance and would have been continuous at the Texas border in the absence (presence) of home equity restrictions. Under this assumption mortgage default outcomes of homeowners in close proximity outside the Texas border are valid no-home-equity-restriction counterfactual outcomes for homeowners on the Texas side.

able to precisely manipulate their location and move across the border simply to self-select out of the treatment group affected by Texas home equity restrictions Lee and Lemieux (2010).[17] Before presenting informal tests of the key identification assumption, I next examine the baseline evidence of discontinuity of discontinuity in nonprime mortgage default rate.

Baseline RD Estimates

Table 2 reports baseline RD estimates of the Texas policy by regressing county-level mortgage default rates on a linear RD polynomial in distance to the Texas border. The coefficient on the Texas dummy measures the extent of discontinuity in the mortgage default rate at the Texas border and can be interpreted as the causal effect of the policy difference on Texas side of the border. To ensure that default outcomes of individuals outside Texas are valid counterfactuals for those on the Texas side, the sample is restricted to sufficiently narrow bands of 25 to 100 miles on both sides of the Texas border.

Unshaded (odd numbered) columns of Table 2 do not include any covariates other than year effects. The shaded (even numbered) columns report estimates from a parsimonious model consisting of three key predictors of mortgage default—the county unemployment rate, 1-year lagged log house price change ($Lagged\Delta HPI$), and county-level initial FICO score.[18] Panel A reports county-level baseline RD estimates for all mortgages (from the LPS database) and Panel B for nonprime mortgages (from the ABS database). Table 2 shows that default rates on all mortgages are about 2-3 percentage points lower within 25 to 100 miles on the Texas side of the border. The discontinuity in nonprime default rates is significantly larger than that for all mortgages—about 3-8 percentage points lower on the Texas side.

The extent of discontinuity generally increases in models with covariates. This is not surprising because mortgage default rates in Texas are expected to be even lower once we account for the state's higher unemployment rate. Overall, the baseline estimates in Table 2 indicate statistically significant evidence of discontinuity as one crosses into the Texas side of the border and the RD estimates are particularly large for nonprime mortgages.

Graphical RD evidence

[17] Indeed as discussed in Lee and Lemieux (2010) if homeowners on the Texas side exercise only imprecise control then the RD design generates a treatment variation close to the border that is as good as randomized experiment or a randomized instrument.

[18] Note that $Lagged\Delta HPI$ is used because contemporaneous values of ΔHPI may be endogenous.

Figure 3 presents graphical evidence of discontinuity in nonprime default rate by plotting the means for each discrete value of the running variable, distance from the Texas border, together with fitted lines on both sides of the border. The sample is restricted to counties within narrow bands of 25 to 100 miles on both sides of the Texas border. The difference in the intercept of the fitted lines represents the RD estimate of the Texas policy's impact on default rates. Based just on raw data without any adjustment for differences in baseline covariates, the scatterplot appears noisy but the cloud of scatter points for each distance band on the Texas side is lower than that across the border.

To reduce noise, Figure 4 plots binned conditional means for 5-mile wide bins—conditional on the unemployment rate, lagged house price change, and initial FICO score. Figure 5 further smooths the data by increasing the bin width to 10 miles and plotting conditional means for 50- to 150-mile bands around the Texas border. Linear fitted lines are based on regression of county level mortgage default rate (adjusted for the baseline covariates) on a linear polynomial in distance.[19] Large difference in intercepts of the linear fitted lines in Figures 4 and 5 present a strong visual evidence of discontinuity in default, similar in magnitude to numerical baseline estimates for nonprime default rates in Table 2. Figures A1 and A2 in Appendix A show that the extent of discontinuity is similar using quadratic rather than linear fits used in Figures 4 and 5.

As a further robustness check, rather than form bins of pre-specified width of 5 or 10 miles, Figure A3 shows visual evidence of discontinuity for 50- to 200-mile bands around the Texas interstate border by selecting bins using IMSE-optimal evenly spaced method in Calonico et al. (2014a, 2015). The extent of discontinuity in binned scatterplots as well as quadratic fits appears similar to those in Figures A1 and A2. Although there is significant evidence of discontinuity in the county-level nonprime mortgage default rate, identification relies on other unobserved factors evolving continuously with respect to the minimum distance to the Texas border. I next present informal tests of the key identification assumptions.

Continuity in other baseline covariates

Figures 6 and 7 show whether other baseline covariates changed continuously on the Texas interstate border, relative to the large discontinuity observed in mortgage default rates. To minimize bias the figures should have been ideally based on data within 25-miles around the Texas border but confidence intervals would be excessively noisy. As a practical compromise between bias and

[19] To plot a fitted line conditional on other covariates, as suggested in Lee and Lemieux (2010), county-level mortgage default rates are first residualized by subtracting the prediction from a regression on other baseline covariates. Then the residualized version is regressed on the linear polynomial on distance to get the fitted line.

variance, this analysis is based on all counties within a 50-mile band. Conditional means for each 5-mile bin and linear fitted lines for the outcome variable (nonprime default rate) are plotted in the top left panel of Figure 6. The remaining three panels show binned means and linear fits for the three key baseline covariates: county unemployment rate (top right), initial FICO score (bottom left) and 1-year change in county level CoreLogic House Price Index (bottom right). Figure 6 and the plotted confidence intervals show that the discontinuity is most pronounced for the outcome variable and rather unnoticeable for potential baseline covariates, except for the unemployment rate.

Figure 7 shows a plot similar to Figure 6 for nonprime default rates (top left) with three measures of lending standards in the remaining panels: mortgage denial rate, debt-to-income ratio, and share of subprime originations. The shaded 95 percent prediction interval around the fitted lines shows that only the discontinuity in the nonprime default rate is statistically significant. To address the concern that mortgage default rates in Texas could be lower simply due to more conservative lending standards, Figure A4 in Appendix A provides a closer look at potential discontinuity in four different measures of mortgage denial rate based on income categories. The overlapping confidence intervals around the linear fits on either side of the discontinuity threshold in all four panels of Figure A4 suggest that there is no evidence of discontinuity in measures of lending standards.

Overall, Figures 6-7 show that the discontinuity in nonprime default rates is significantly more noticeable than that in other baseline covariates.[20] The unemployment rate is a notable exception that displays significant discontinuity. Nevertheless, a higher unemployment rate in Texas will bias downward the magnitude of the policy's estimated impact on mortgage default rates in specifications not explicitly controlling for the difference in unemployment rates. Therefore, in all remaining specifications in the paper I explicitly control for the unemployment rate among other covariates.

4.2 County level Multidimensional RD Framework

While traditional one-dimensional RD specifications provide compelling evidence of the Texas policy's effect on mortgage default, recent research has proposed a multidimensional approach to implement boundary RD design methods of the type used in this paper (Dell, 2010; Zajonc, 2012). In this case, the discontinuity threshold is a multidimensional discontinuity in latitude and longitude space. The multidimensional RD approach potentially uses more information and

[20] Using IRS data on state-to-state migration of tax returns, Table A2 in Appendix A presents tentative evidence that borrowers did not manipulate their location in response to the 1997 amendment that eased access to home equity.

contains more variation than a one-dimensional method that uses distance alone as the running variable. In this framework the running variable is a multidimensional RD polynomial in latitude (X) and longitude (Y), denoted ($\sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q}$).[21] Because the multidimensional RD polynomial varies only with county, I estimate the following specification based on county-year level data, weighting estimates by number of mortgages and clustering standard errors at the county level to account for serial correlation:

$$PctMortDefault_{cst} = \beta_0 + \beta_1 Texas_s + \sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q} + \gamma Z_{cst} + d_t + u_{cst} \tag{2}$$

In estimating equation (2), I go beyond the baseline specification in (1) and include a richer set of covariates in Z_{cst}, with their choice guided by previous research that found negative equity, mortgage affordability, and liquidity constraints are the key determinants of mortgage default (Campbell and Cocco, 2011; Elul et al., 2010). In addition to the three key covariates—the county unemployment rate, 1-year lagged annual house price change ($Lagged\Delta HPI$), and county-level initial FICO score— included for baseline estimates in Table 2, I account for whether the initial LTV (CLTV in ABS data) was 80 percent or higher, county level log median household income, share of adjustable rate mortgages, share of cash-out refinance mortgages, and average county-level mortgage denial rate between 2000 and 2006.[22] Finally, I also account for state border specific characteristics (α_b) by including dummies for three of the four state border segments: TX-AR, TX-LA, TX-NM, TX-OK.

LASSO selection of RD polynomial terms

The previous literature typically has used linear, quadratic, or cubic specification for the multidimensional RD polynomial ($\sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q}$). The tradeoff involved in selecting a low vs. a high order RD polynomial is well-known. A high order polynomial can have a large number of terms and can easily result in overfitting and imprecise estimates, particularly if estimation is

[21] $P = Q = 3$ with $p + q \leq 3$ in $\sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q}$ dropping all redundant terms would yield a cubic polynomial.

[22] Because the treatment variable ($Texas_s$) mainly represents variation in home equity extraction, initial LTV and house price growth account for any role of negative equity other than that through home equity extraction. In alternative specifications, I included the 1-year lag or 1-year change in the unemployment rate, and the interaction of the unemployment rate and $Lagged\Delta HPI$. The results were almost identical. I do not control for other unorthodox features of mortgages –e.g., negative amortization, interest-only mortgages, balloon mortgages etc.—as there may not be enough variation in close band around the border. Moreover Mayer et al. (2009) found that they did not significantly affect default rates. The default decision is also correlated with interest rates and expected house price change (Bajari et al., 2008). While fixed rate mortgages are more likely to default if the spread between the current and original mortgage interest rate is high, the opposite holds true for adjustable rate mortgages (ARM) (Campbell and Dietrich, 1983). But interest rates and expected house price are not much of a concern here as they would not vary significantly around the border.

restricted to data close to the discontinuity threshold, while a low order polynomial can lead to biased estimates. To dispense with arbitrary selection of the number of terms in the multidimensional RD polynomial, I use the recently proposed post-double-LASSO treatment effect estimator from Belloni et al. (2014a). A number of recent papers have shown that LASSO is an appealing and computationally efficient method to estimate parameters in high-dimensional models Belloni et al. (2012, 2014b) . LASSO minimizes least-square errors subject to a constraint on the sum of absolute value of coefficients. The penalty level (λ) is a key parameter that determines the parsimony or the number of nonzero coefficients in the model. A high λ selects parsimonious models by setting weakly correlated terms to zero, while a small λ yields models with large number of terms; $\lambda = 0$ yields the OLS specification. As described in Appendix C, I select λ based on practical guidelines and procedures in Belloni et al. (2014a) and explore the sensitivity of estimates to different choices of λ.

Results using LPS database on all mortgages

Table 3 reports multidimensional RD estimates of the effect of the Texas policy on the mortgage default rate based on the model with an extensive set of covariates, presented in equation (2). Estimates are based on county-year level data on all residential mortgages. The top three panels present estimates from linear, quadratic, and cubic polynomials in latitude and longitude, respectively. Overall, Table 4 suggests that the Texas policy is associated with significantly lower mortgage default rates of about 1 to 1.5 percentage points—plausibly by curbing home equity extraction and limiting negative equity. The effect is economically significant as the average default rate for all mortgages in Texas between 2007 and 2011 is just about 4 percent. The bottom panel shows estimates from multidimensional RD applied in combination with the post-double-LASSO treatment effect estimator from Belloni et al. (2014a) presented in equation (5). Using LASSO to choose terms from a fourth order multidimensional RD polynomial yields a parsimonious model with 1-3 terms for various distance bands around the Texas interstate border. LASSO results are qualitatively similar to other estimates in Table 3 and essentially show that results are robust to using a model that is partially linear in spirit.

Results for nonprime mortgages using ABS database

Using all residential mortgages could understate the true impact of the Texas policy on mortgage default if some homeowners with mortgages in Texas were either not or only partially affected by the policy.[23] Nonprime borrowers are more intensely affected by the Texas' policy as they are likely to be closer to the 80 percent combined LTV threshold. Moreover, scatterplots and fitted lines in Figure A5 (Appendix A) suggest that the policy appears to have successfully inhibited cash-out refinancing—a primary channel of home equity extraction—among nonprime borrowers in Texas. Simple difference in means presented in Table 1 and simple linear RD regression estimates in Table A3 show that the share of mortgages more than 20 percent underwater are generally lower in Texas, although some estimates are imprecise as the data is available only for a limited number of counties.[24]

Table 4 repeats the exercise in Table 3 using data on nonprime mortgages and provides cleaner estimates of the impact of policy discontinuity across the Texas border. The estimated Texas policy discontinuity is statistically significant and remarkably robust across different polynomial specifications and suggests that the Texas policy lowered nonprime mortgage defaults by 4-5 percentage points. The impact is about four times as large as the estimated impact using LPS data on all residential mortgages in Table 3. The effect is economically significant as the average nonprime default rate in Texas between 2007 and 2011 is just about 12 percent.

Due to space constraints, further robustness checks of the county-level estimates are presented in Appendix A. I start with checking robustness with respect to state-level differences in legal and institutional arrangements. While all five states in the estimation sample are recourse states and allow deficiency judgment, some differences exist. For example, Louisiana, Oklahoma, and New Mexico require a judicial foreclosure process, while Texas and Arkansas do not. New Mexico is the only state in the sample that provides the right of redemption. Table A4 shows that estimated effects are robust to controls for state-specific policy differences.[25] Table A5 examines sensitivity to nonparametric methods in Calonico et al. (2014b). Table A6 shows that estimates are robust to restricting the estimation sample to contiguous border counties (Dube et al., 2010).

[23] For example, the home equity restriction may not be fully binding on homeowners who already had sufficient equity in their homes. Mian and Sufi (2011) found that homeowners in the bottom quartile of the credit score distribution did much of the borrowing against housing wealth during the house price boom, while those in the top quartile were far less likely to extract home equity. Pennington-Cross and Chomsisengphet (2007) found that roughly half of refinancing by subprime borrowers were for cash-out—almost twice as likely as prime borrowers—and 85 percent of subprime refinances with fixed rate mortgages engaged in cash-out refinancing from 1996-2003.

[24] Data on negative equity is from CoreLogic TrueLTV database available from RADAR data warehouse. I must acknowledge that negative equity calculations in this database are based on several model assumptions that limit its reliability. The data has gaps and is also not available for all counties, just the larger counties.

[25] Judicial foreclosure process is apparently the most pervasive difference between Texas and the bordering states. Therefore, the finding is consistent with Vicente (2013), that also finds no impact of judicial process on delinquency.

Additionally, using the interstate borders of the remaining 47 contiguous states as placebo borders, placebo tests presented in Appendix B bolster the conclusion that the Texas policy indeed significantly lowered nonprime mortgage defaults.

Results by origination year

The results presented in Table 4 do not distinguish between mortgage vintages. Recent research has documented exceptionally poor performance of 2006 and 2007 vintage loans, suggesting that underwriting criteria deteriorated significantly for mortgages that originated in the "go-go" years near the peak of the housing boom.[26] If so, then part of the estimated impact in Table 4 could simply be due to relatively more lax lending standards in neighboring states driving up nonprime default rates relative to Texas.

Focusing on counties within 50 miles of the Texas border, Figure 8 shows that initial CLTV and debt-to-income (DTI) climbed, while the share of cash-out refinances declined both in Texas and bordering states for vintages leading up to the housing boom.[27] The higher DTI ratio in Texas partly assuages the concern that lenders were more conservative than those just across the border. Figure 8 also reinforces the finding in Figure A5 and shows that Texas' mortgages remained significantly less prone to being used for cash-out across all vintages. Importantly, the Texas-bordering state differential in key mortgage characteristics remained small and largely stable as the housing market gained steam.

To shed more light on the important drivers of the Texas-bordering state differential in nonprime default rates, Figure 9 plots the estimated coefficient on the Texas dummy for three different specifications and shows that the coefficient remained negative for all vintages except the 2001 vintage. Adding measures of lending standards (DTI ratio and mortgage denial rate) to the baseline specification raises the policy's estimated impact.[28] Adding the share of cash-out refinancing mortgages to the regression significantly weakens the estimated effect, confirming the intuition that much of the policy's impact operated through its role in restraining cash-out mortgages in Texas relative to other states.

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[26] Demyanyk and Van Hemert (2011) found that loan quality deteriorated progressively between 2001 and 2007 as combined LTV increased. Lax lending standards contributed to proliferation of increasingly risky high-LTV borrowers. Bayer et. al. (2013) found that the black-white differential in mortgage default spiked as the housing market peaked in 2006 and minority homeowners with high debt-to-income ratio were particularly at risk of default on mortgages that originated between 2004 and 2006.

[27] Plots look similar for other distance bands on either side of the Texas border and are available on request.

[28] This is not surprising because both measures suggest that lending standards in Texas were somewhat less stringent.

Figure 9 also shows that the policy's estimated impact is significantly stronger for vintages 2002 and after, and there are no spikes in 2006 or 2007. A weaker estimated effect for vintages leading up to the housing boom further alleviates the concern that lending standards became more lax just across the border from Texas as the housing market peaked. Results on county-level mortgage defaults presented so far do not distinguish between the incidence of default and the duration before mortgages default. Using loan-level data I next examine whether the Texas policy lowered mortgage default hazards.

4.3 Duration models using loan-level ABS data on nonprime mortgages

Nonparametric survival probabilities

Figure 10 compares simple nonparametric Kaplan-Meier survival probabilities of Texas' nonprime mortgages with those from bordering states within 50 miles of the Texas border. The top left panel shows that survival probabilities, overall, were uniformly higher among nonprime mortgages in Texas at all durations. The remaining three panels show that survival rates in Texas are higher than bordering states for all three vintages shown in Figure 10, but the difference is larger for the 1998-2000 and 2001-03 vintages.[29] Going beyond simple comparisons in Figure 10, I now examine the policy's impact on mortgage default hazards using multidimensional RD specifications.

Cox proportional hazard model with RD using loan-level data on nonprime mortgages

The following hazard model for mortgage default is estimated using Cox Proportional Hazard framework of the form:

$$\psi(t|X_{icst}, \beta) = \psi_0(\mathrm{t}) \exp\{X_{icst}\beta\} \quad (3)$$

In equation (3), i indexes loans, $\psi(t|X_{icst}, \beta)$ is the hazard rate of mortgage default in month t given that the borrower has not defaulted until month $t-1$, $\psi_0(\mathrm{t})$ is the baseline hazard function that depends on duration t. The term $\exp(X_{icst}\beta)$ captures the impact of covariates on the mortgage default hazard. Analogous to equation (2), the specification for Cox proportional hazard model takes the following form in a multidimensional RD framework:[30]

$$\psi(t|X_{icst}, \beta) = \psi_0 \exp\{\beta_0 + \beta_1 Texas_s + \sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q} + \gamma Z_{icst} + d_t + u_{icst}\} \quad (4)$$

[29] The larger difference in survival rate between Texas and bordering states for 2001-03 vintages relative to 2004-06 is broadly consistent with the pattern in cash-out refinancing activity. The Texas policy likely kept at bay a strong surge in cash-out refinance mortgages from 2001 to 2003, a trend that ebbed somewhat between 2004 and 2006 (Demyanyk and Van Hemert, 2011; Khandani et al., 2013).

[30] See Card et al. (2007) for a similar specification using standard RD approach.

The vector Z includes key county-level covariates: unemployment rate, 1-quarter $Lagged\Delta HPI$, log median household income, and pre-2007 mortgage denial rate; and loan-level characteristics: initial FICO score, whether the initial CLTV was 80 percent or higher, adjustable-rate mortgage, and whether the loan purpose was cash-out refinance. Additionally, I control for year and month effects, and origination year effects. Because $\sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q}$ and some baseline covariates vary only at the county level, the standard errors in estimation of (4) are clustered at the county level.

Table 5 reports Cox proportional hazard estimates in a form similar to county-level RD estimates presented in Table 4 and shows that mortgage default hazards are significantly smaller on the Texas side of the border when the sample is restricted to narrow bands around the border.[31] The coefficient on the Texas treatment dummy can be interpreted as percent difference in nonprime mortgage default rates between Texas and neighboring states.[32] Comparing mortgages within 25 miles on either side of the Texas border, column (1) shows that the Texas policy lowered nonprime mortgage defaults by 10-20 percent but results are imprecise. Precision improves with wider distance bands that use more data and estimates turn significant. Overall, Table 5 indicates a strong negative effect of the Texas policy on nonprime mortgage default hazards in a close neighborhood on both sides of the border and the estimated impact ranges from 13 to 28 percent with a midpoint of about 20 percent.[33]

5. Conclusion

It is now widely believed that aggressive home equity extraction by borrowers with inadequate ability to service unaffordable debt helped precipitate the subprime mortgage crisis. Regulations to curb excessive mortgage debt have long existed in other countries but Texas is the only state in the US that limits home equity borrowing to 80 percent of home value. Anecdotal reports have suggested that Texas' limits shielded homeowners from the worst of the subprime mortgage crisis. However, there remained no formal empirical investigation of the regulations' role in curbing mortgage default in Texas. This paper is the first to empirically estimate the impact of

[31] The coefficient on the Texas treatment dummy from Cox proportional hazard model equals the log of mortgage default hazard ratio of Texas to Non-Texas and can be roughly interpreted as percent change in mortgage default hazard as one moves to Texas side of the border.

[32] The exponential of the coefficient on the Texas treatment dummy from Cox proportional hazard model has the interpretation of the impact of a covariate on the hazard ratio of mortgages in Texas relative to those across the border in neighboring states.

[33] For hazard model estimation loans were followed up from origination to either default or non-default until the end of the sample period in 12/2011 for a maximum period of 153 months. All non-defaulting loans were treated as right-censored. The survival data is single spell with right-censoring. RD polynomial terms used in the LASSO specification of Cox model reported in Panel D of Table 5 are chosen using simple linear regressions.

Texas home equity restrictions on mortgage default using loan level data from two different sources. The paper exploits the policy discontinuity around the Texas' interstate borders, induced by Texas' home equity restrictions, to identify the causal effect of home equity extraction on mortgage default in a spatial RD framework.

In addition to the standard one-dimensional regression discontinuity design (RD) setup, I employ a multidimensional RD approach from Dell (2010) and model the Texas border with neighboring states as a multidimensional discontinuity in latitude and longitude space. Because a suitably flexible multidimensional RD polynomial can be high-dimensional, I combine this method with recently proposed post-double-LASSO treatment effect estimator from Belloni et al. (2014a) to estimate the impact of Texas home equity restrictions on mortgage default.

The paper finds that the Texas home equity restrictions lowered the likelihood of default for all residential mortgages by about 1 percentage point between 2007 and 2011. This effect is economically significant, considering that the share of individuals defaulting in the data is just about 4.3 percent, on average from 2007 to 2011. The paper also finds that the Texas policy of restricting home equity extraction had a much larger impact on nonprime mortgage default rates of about 4-5 percentage points, also a sizeable effect relative to the average 13 percent nonprime default rate between 2007 and 2011. Estimated default hazards for mortgages within 25 to 100 miles of the Texas' borders decline by about 20 percent as one crosses into the Texas side of the border. Overall, the paper finds evidence that Texas' home equity restrictions negatively affected mortgage default—a finding that is robust to use of aggregate state level data as well as detailed loan level data.

These findings are consistent with simulation evidence in Laufer (2011)—the only other paper to have considered the effect of a Texas-style policy—which found that home equity borrowing restrictions lowered default by 28 percent and was welfare-enhancing. My findings have important policy implications for the effectiveness of potential future regulations to curb excessive mortgage debt. The findings suggest that policies to curb excessive home equity extraction by capping LTV can, indeed, lower eventual default. Such policies can be effective substitutes for costly loan modification policies followed previously.[34] My findings also suggest that such policies may be particularly effective in curbing mortgage defaults among nonprime borrowers. Nevertheless, this paper is unable to shed light on the effectiveness of regulations to limit debt-to-income ratios that address incidence of mortgage defaults due to liquidity constraints (Bajari et al.,

[34] See Foote et al. (2008) for costs associated with loan modification policies.

2008; Campbell and Cocco, 2011). Given the strong role of negative equity, liquidity constraints, as well as their interaction in precipitating default, it may well be optimal to pursue a combination of policies to prevent future turmoil.

Although, overall, my findings point to potential benefits from such regulations, attendant costs of such policies and some caveats must be kept in mind. While mandatory caps on home equity borrowing helped Texas curb mortgage defaults, the limits also could hurt long-term economic growth by impeding consumer spending during a housing boom,[35] preventing homeowners from optimally utilizing their home equity and tightening liquidity constraints Engelhardt (1996b). Second, as Laufer (2011) noted, such policies reduce the value of housing collateral and could contribute to smaller house price gains in Texas, relative to other states, further eroding its benefits. As mentioned earlier, the Texas restrictions unintendedly push credit-constrained individuals to more expensive credit card debt or even more exorbitant payday loans. A more comprehensive empirical analysis of the policy's likely costs is left to future research.

[35] Abdallah and Lastrapes (2012) found that by allowing home equity borrowing and relaxing credit constraints, Texas' 1997 constitutional amendment had a significantly positive impact on consumer spending. Although, they did not study the impact of the 80 percent cap on home equity extraction, their findings would imply that Texas-style caps on home equity borrowing would hurt consumption during times of economic and housing boom.

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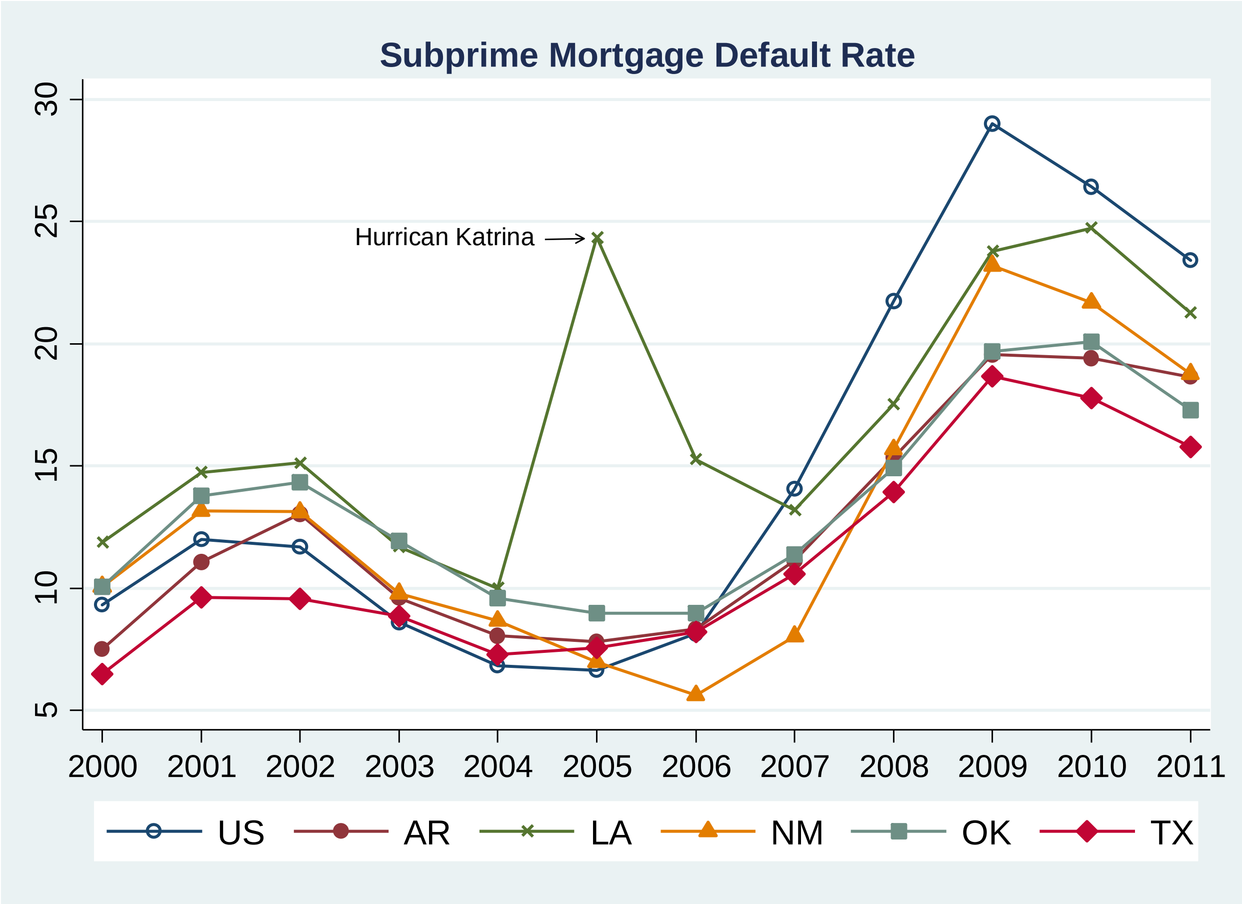
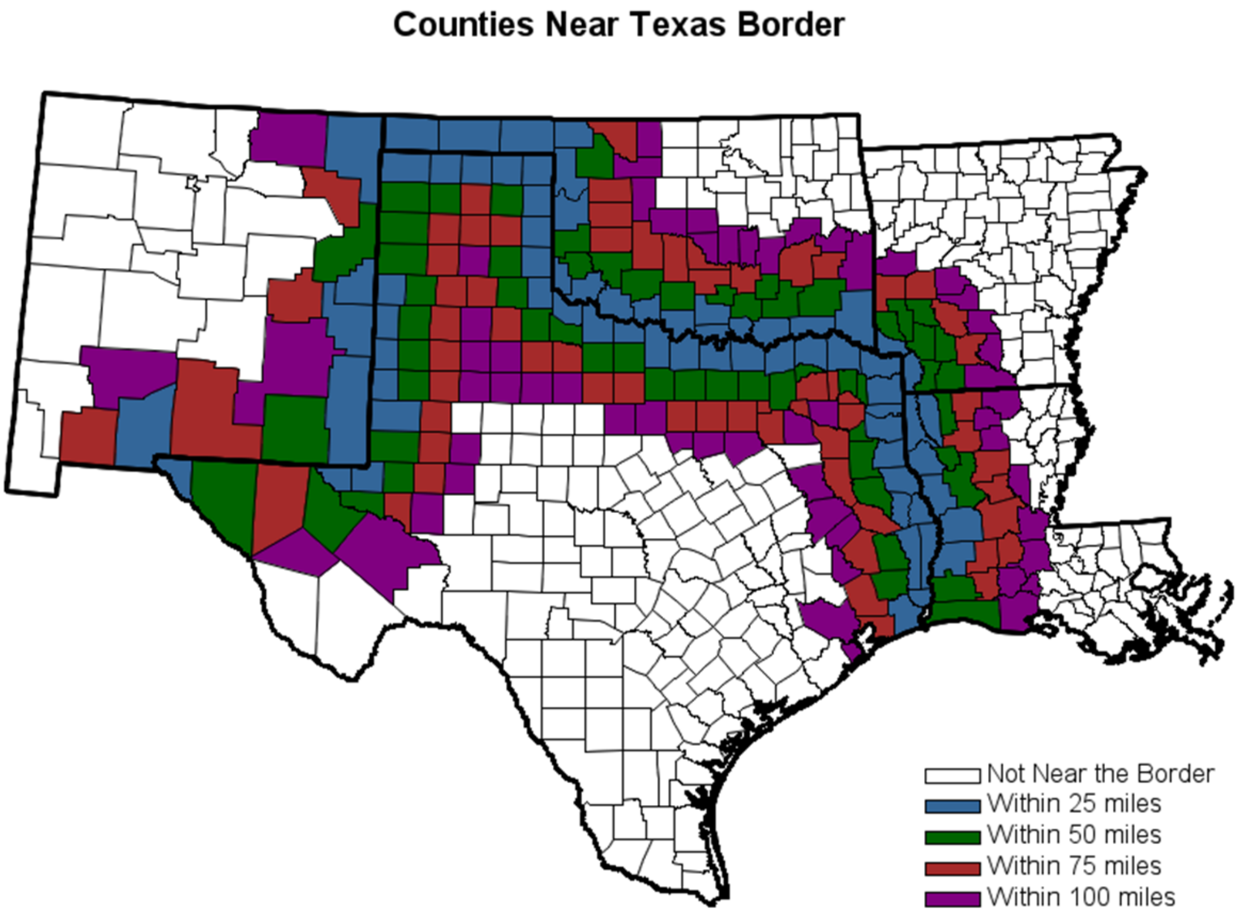
Figure 1



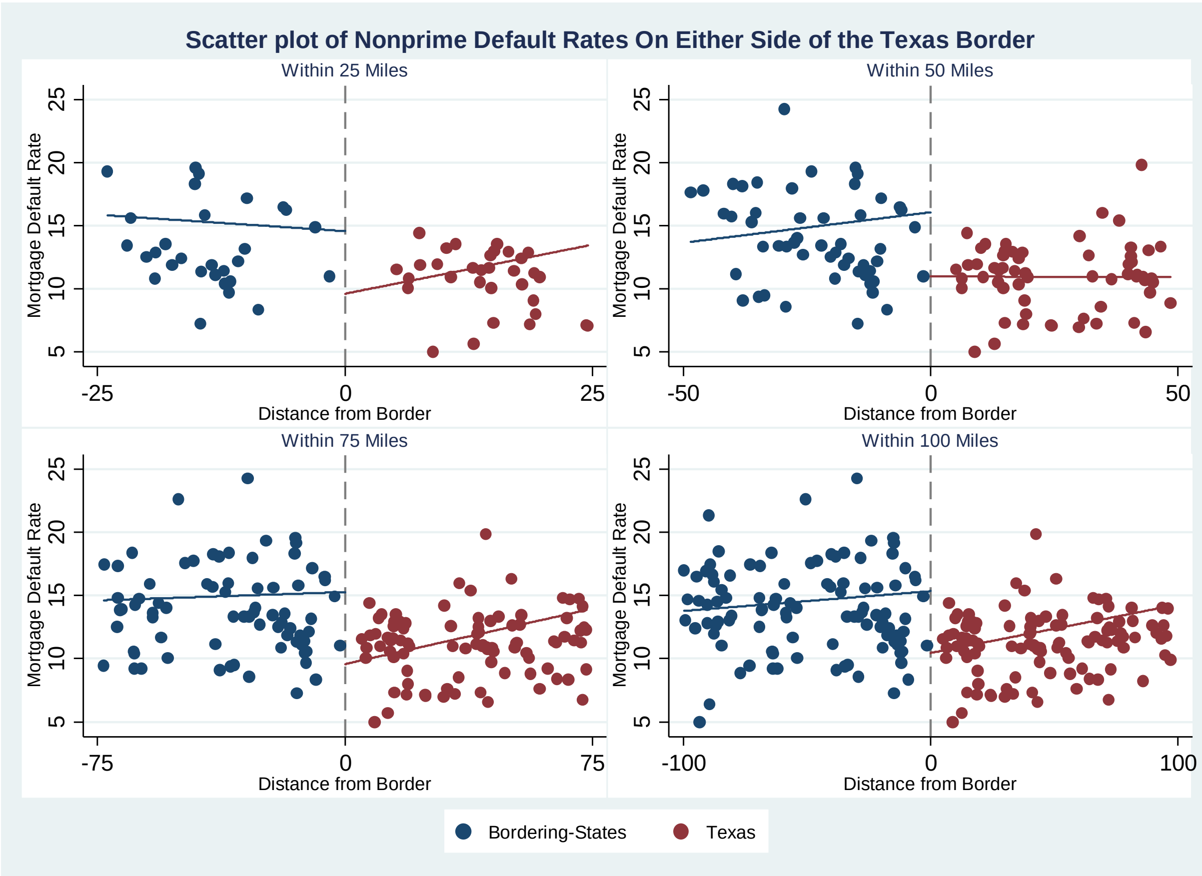
Note: Subprime mortgage default rates plotted in the chart are percent of subprime mortgages 90 plus day or in foreclosure inventory from Haver Analytics based on data from Mortgage Bankers Association.

Figure 2



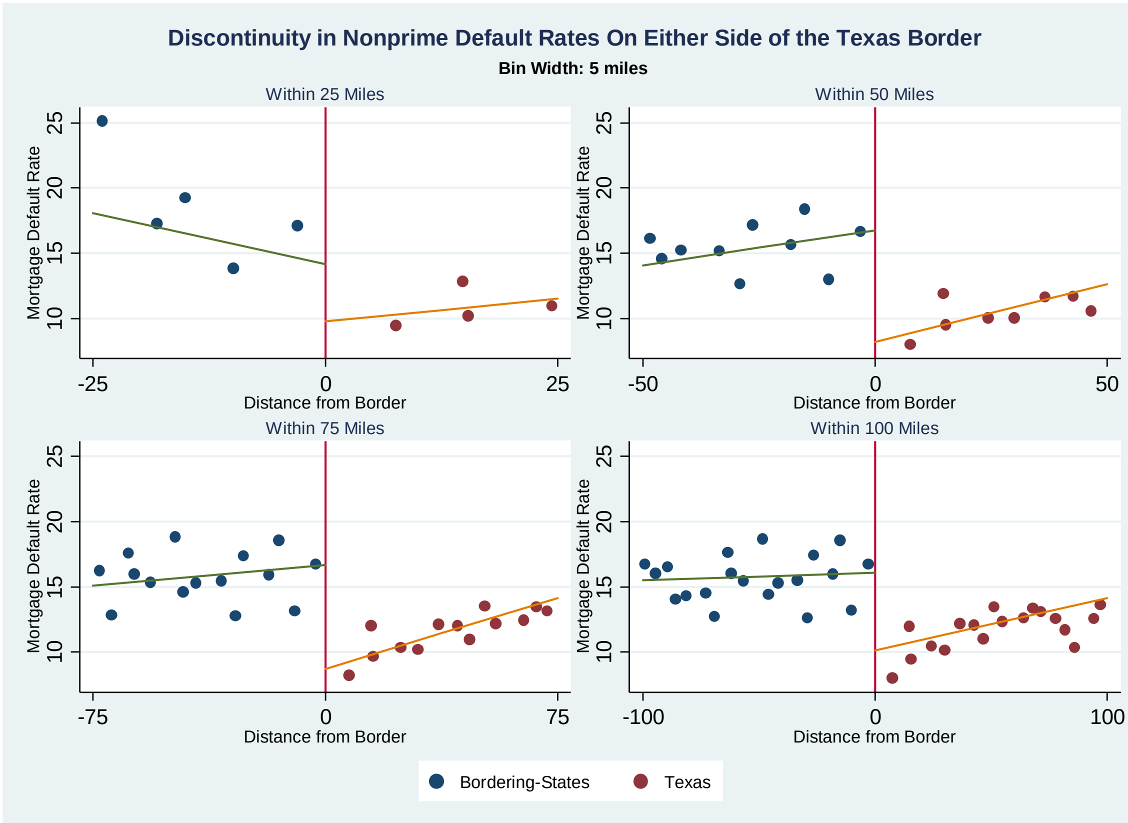
Counties Near Texas Border
Not Near the Border
Within 25 miles
Within 50 miles
Within 75 miles
Within 100 miles

Figure 3



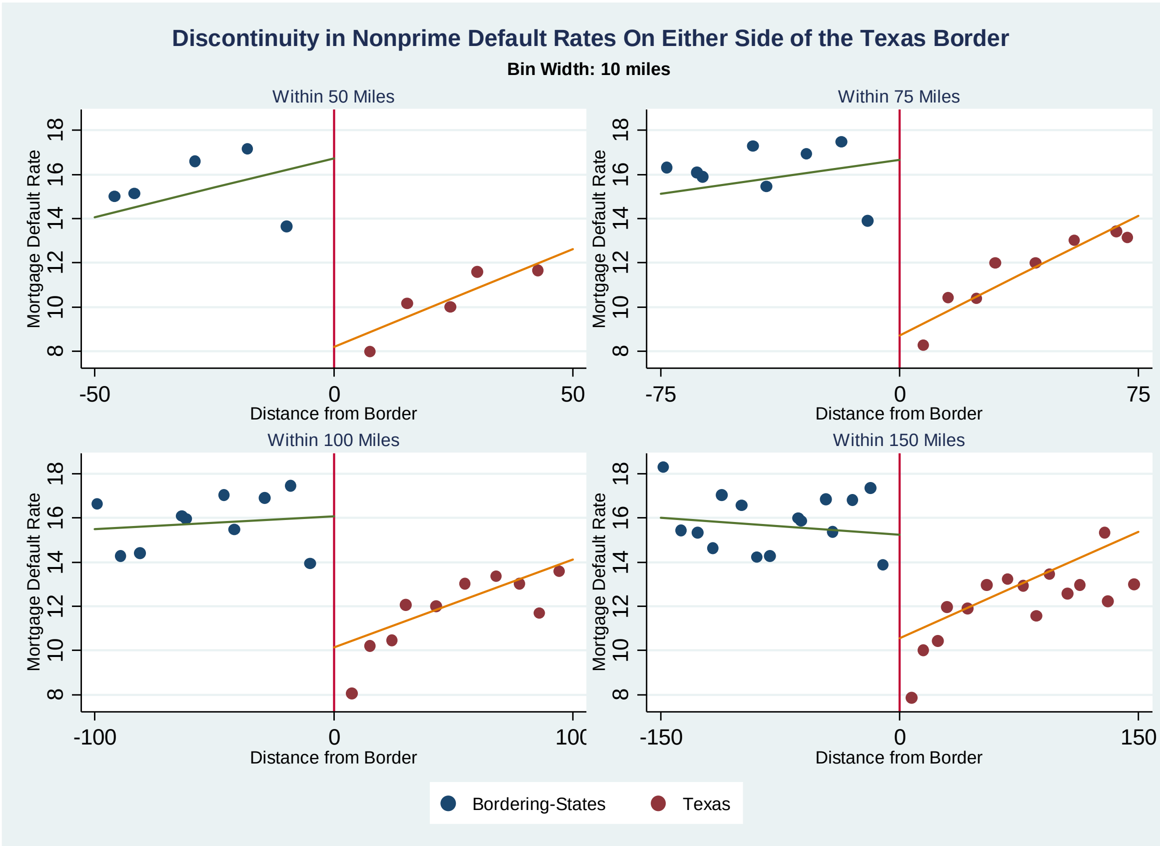
Note: The figure plots average county-level nonprime mortgage default rates from 2007 to 2011 for each discrete value of minimum distance from the Texas border (normalized to zero at the border). The plots are based on author's calculation using ABS data from RADAR Data warehouse. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). Linear fitted lines are based on regression of 2007-2011 average of county level mortgage default rate on a linbear polynomial in distance weighted by numer of nonprime loans.

Figure 4



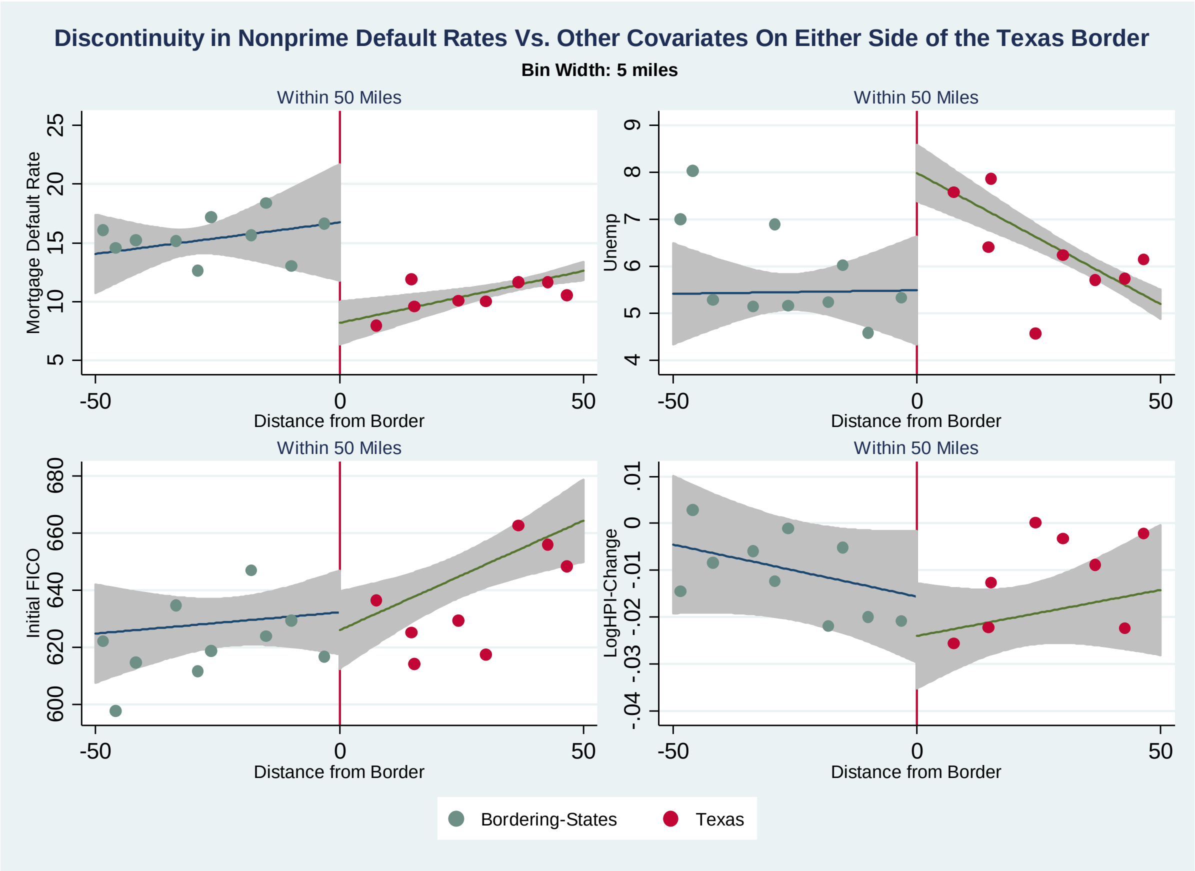
Note: The figure plots conditional mean of county-level nonprime mortgage default rate from 2007 to 2011 (controlling for baseline covariates: unemployment, initial FICO, and house price change) within 5-mile wide bins. Linear fitted lines are based on regression of county level mortgage default rate (residualized by subtracting the prediction from a regression of mortgage default rate on baseline covariates) from 2007 to 2011 on a linear polynomial in distance. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). All estimates are weighted by county-level number of nonprime loans. Sources of data are: County-level nonprime default rate and initial FICO calculated using ABS data from RADAR Data warehouse; county unemployment rate from BLS/LAUS; county-level house price index from CoreLogic.

Figures 5



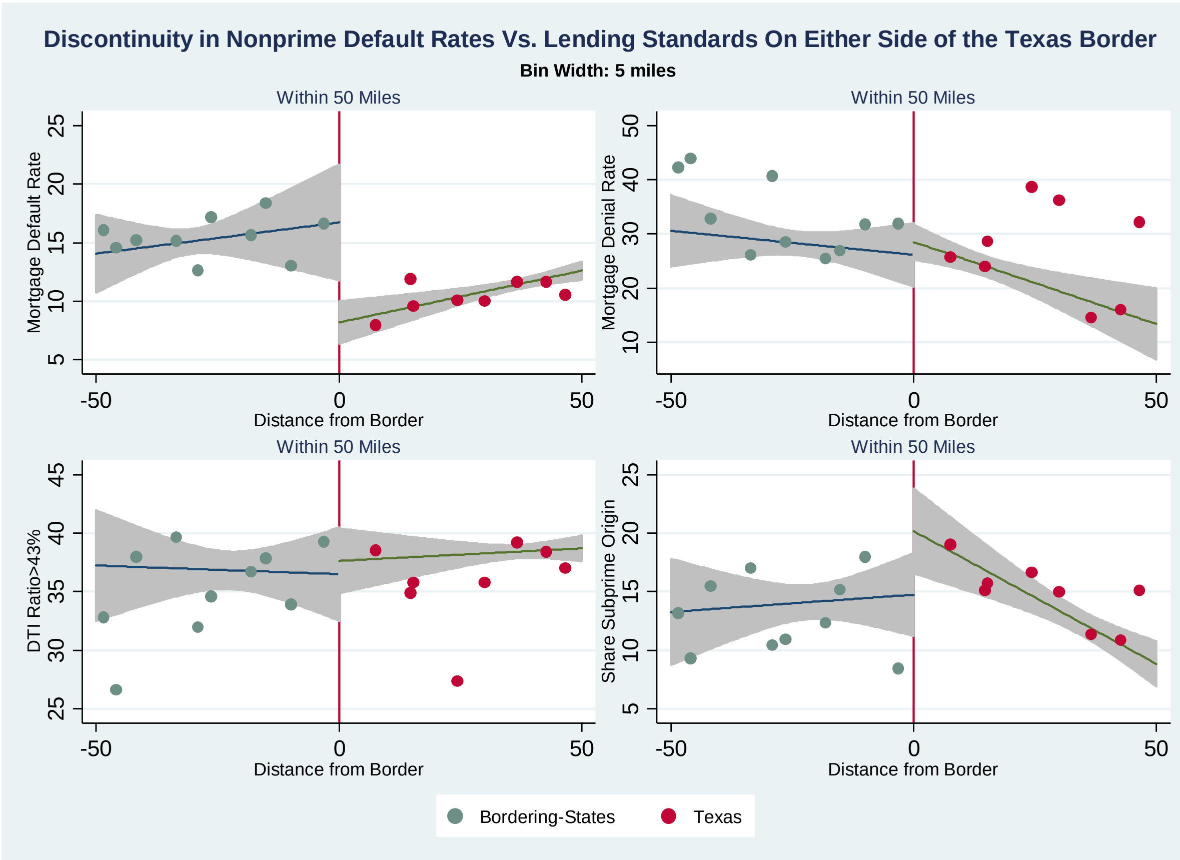
Note: The figure plots conditional mean of county-level nonprime mortgage default rate from 2007 to 2011 (controlling for baseline covariates: unemployment, initial FICO, and house price change) within 10-mile wide bins. Linear fitted lines are based on regression of county level mortgage default rate (residualized by subtracting the prediction from a regression of mortgage default rate on baseline covariates) from 2007 to 2011 on a linear polynomial in distance. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). All estimates are weighted by county-level number of nonprime loans. Sources of data are: County-level nonprime default rate and initial FICO calculated using ABS data from RADAR Data warehouse; county unemployment rate from BLS/LAUS; county-level house price index from CoreLogic.

Figure 6



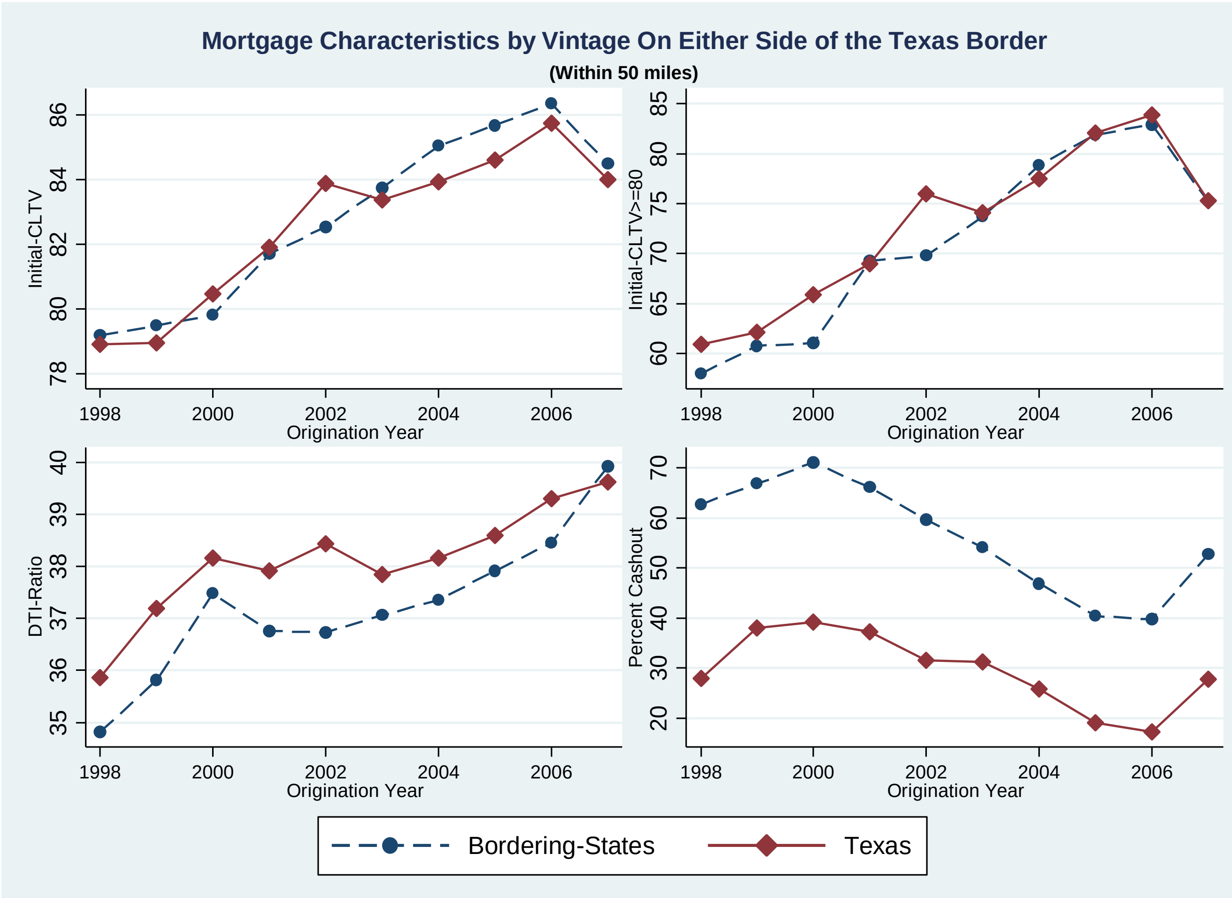
Note: The shaded reagion is 95 percent confidence intervals of the fitted lines. In the top left panel the figure plots conditional mean of county-level nonprime mortgage default rate from 2007 to 2011 (controlling for baseline covariates: unemployment, initial FICO, and house price change) within 5-mile wide bins. Linear fitted lines in the top lefet panel are based on regression of county level mortgage default rate (residualized by subtracting the prediction from a regression of mortgage default rate on baseline covariates) from 2007 to 2011 on a linear polynomial in distance. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). Plots in the remaining three panels are of simple uncodnitional mean of baseline covariates within 5-mile bins. Linear fitted lines in the remaining three panels are from a simple regression of the relevant variable on a linear polynimial in distance. All estimates are weighted by county-level number of nonprime loans. Sources of data are: County-level nonprime default rate and initial FICO calculated using ABS data from RADAR Data warehouse; county unemployment rate from BLS/LAUS; county-level house price index from CoreLogic.

Figure 7



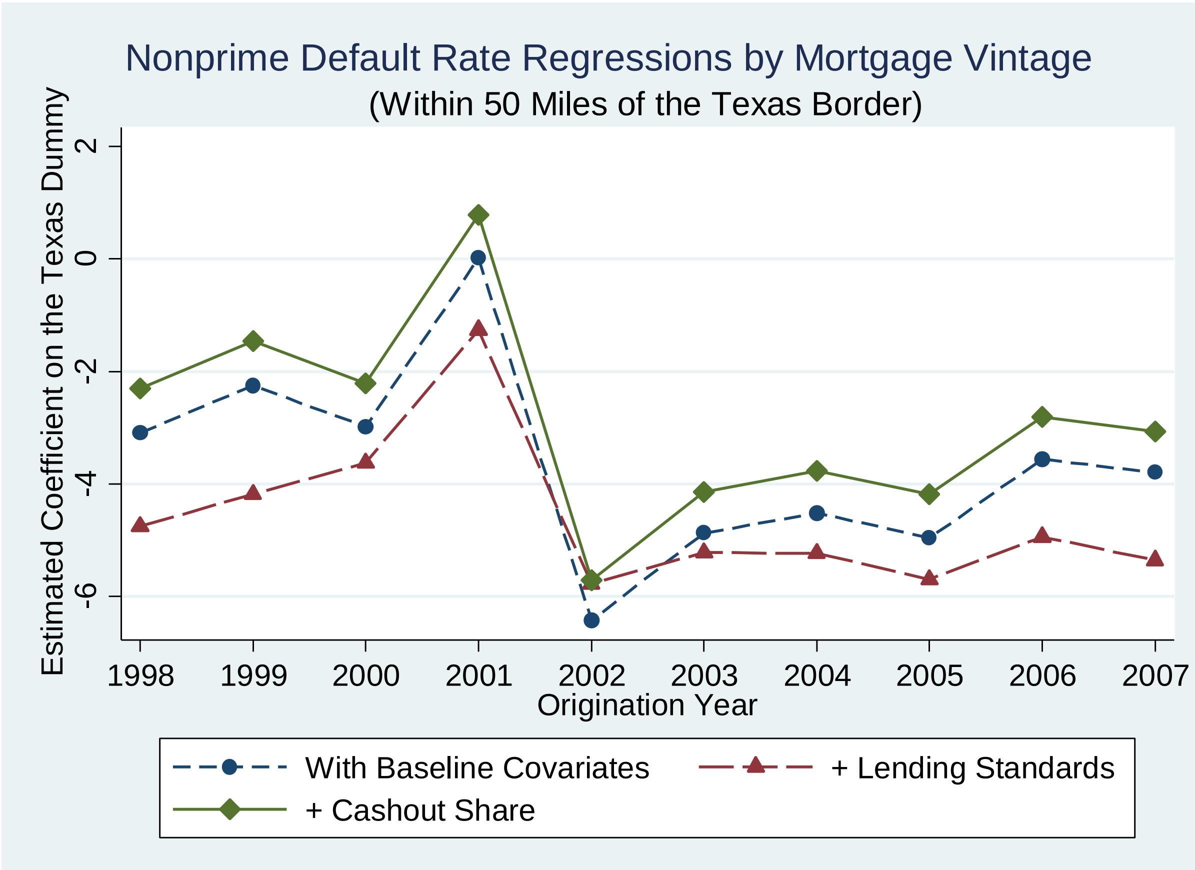
Note: The shaded reagion is 95 percent confidence intervals of the fitted lines. In the top left panel the figure plots conditional mean of county-level nonprime mortgage default rate from 2007 to 2011 (controlling for baseline covariates: unemployment, initial FICO, and house price change) within 5-mile wide bins. Linear fitted lines in the top lefet panel are based on regression of county level mortgage default rate (residualized by subtracting the prediction from a regression of mortgage default rate on baseline covariates) from 2007 to 2011 on a linear polynomial in distance. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). Plots in the remaining three panels are of simple uncodnitional mean within 5-mile bins of measures of lending standards: debt-to-income ratio, mortgage denial rate, and share of subprime mortgage originations. Linear fitted lines in the remaining three panels are from a simple regression of the relevant variable on a linear polynimial in distance. All estimates are weighted by county-level number of nonprime loans. Sources of data are: County-level nonprime default rate, initial FICO, and debt-to-income ratio calculated using ABS data from RADAR Data warehouse; county unemployment rate from BLS/LAUS; county-level house price index from CoreLogic; mortgage denial rate and share of subprime origination are from HMDA.

Figure 8



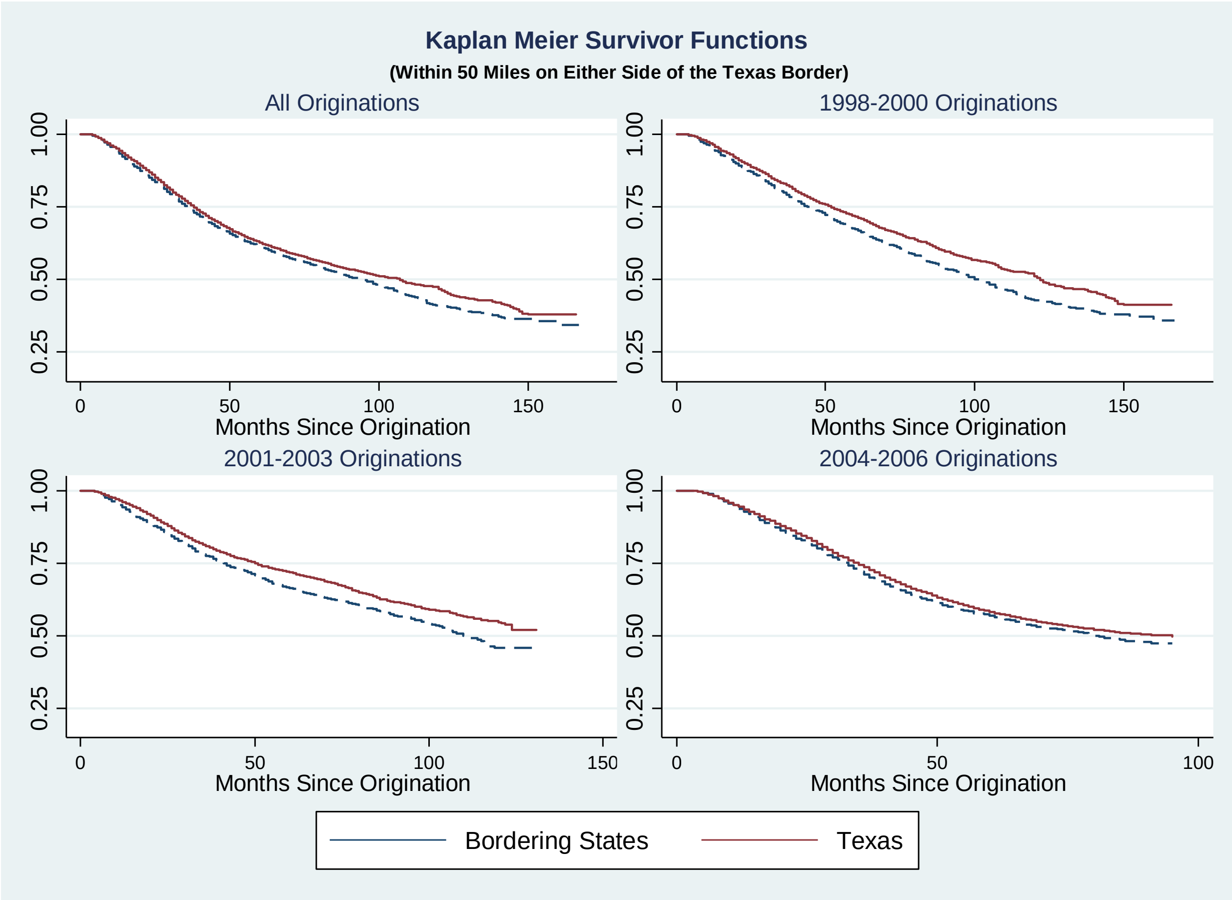
Plotted means of mortgage characteristics are based on county-level data on nonprime mortgages created using ABS database from the RADAR data warehouse.

Figure 9



Estimates based on data on nonprime mortgages from ABS database. Baseline covariates consist of county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, and year effects. Estimates weighted by number of loans in each county-vintage-year cell. The coefficient on the Texas dummy should be interpreted as the difference in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border.

Figure 10



Source: ABS data from RADAR Data warehouse; author’s calculations.

Table 1: Summary Statistics

	25 Miles	25 Miles	50 Miles	50 Miles	All	All
	Texas	Texas *minus* Bordering States	Texas	Texas *minus* Bordering States	Texas	Texas *minus* Bordering States
A: All Mortgages						
Mortgage Default Rate	4.01	-1.04	3.60	-1.45**	4.25	-0.63*
	(1.28)	(0.79)	(1.14)	(0.52)	(1.45)	(0.31)
Initial FICO	684.51	-7.17	700.10	10.48	697.05	-1.77
	(5.90)	(5.28)	(14.72)	(6.75)	(11.75)	(2.63)
B: Nonprime Mortgages						
Mortgage Default Rate	11.09	-4.32*	10.94	-4.06***	12.63	-2.72***
	(4.00)	(1.73)	(3.57)	(1.18)	(3.82)	(0.70)
Share ARM	0.30	-0.04*	0.32	-0.02	0.32	-0.04***
	(0.04)	(0.02)	(0.03)	(0.01)	(0.03)	(0.01)
Percent Cash-out	34.88	-12.47***	23.64	-25.30***	25.32	-20.97***
	(4.49)	(2.14)	(10.13)	(4.02)	(6.41)	(1.29)
DTI-Ratio	38.19	0.31	38.58	0.83**	38.71	1.05***
	(0.86)	(0.36)	(0.72)	(0.26)	(0.60)	(0.15)
Initial FICO	630.89	-1.99	648.62	19.59*	644.32	4.20
	(12.68)	(7.35)	(19.83)	(7.92)	(13.58)	(4.02)
Initial-CLTV	85.75	-1.84*	88.47	0.98	88.13	1.26**
	(0.98)	(0.74)	(2.37)	(1.03)	(1.72)	(0.45)
Initial-CLTV≥80%	76.21	-3.65	82.41	2.65	81.44	2.87*
	(2.60)	(1.98)	(5.41)	(2.43)	(4.13)	(1.16)
Underwater (CLTV≥110)	5.30	-7.94**	9.84	-0.73	15.67	0.82
	(6.69)	(2.72)	(6.44)	(3.04)	(10.47)	(2.39)
Underwater (CLTV≥120)	2.95	-6.99*	4.21	-3.50	7.25	-1.16
	(6.35)	(3.27)	(4.28)	(2.78)	(6.25)	(1.34)
C: Other Characteristics						
HPI-Change(2007-2011)	-0.14	-0.08	-0.11	-0.05	-0.10	-0.02
	(0.02)	(0.07)	(0.03)	(0.05)	(0.04)	(0.02)
Unemp	7.51	2.00***	6.34	0.89*	6.36	0.70***
	(2.11)	(0.39)	(2.00)	(0.44)	(1.93)	(0.16)
LOG-MedHHI	10.57	0.01	10.95	0.37**	10.84	0.18***
	(0.10)	(0.05)	(0.33)	(0.14)	(0.22)	(0.04)
Mortgage Denial Rate	26.30	-0.95	19.60	-8.54**	21.15	-2.31
	(5.24)	(1.65)	(8.42)	(3.15)	(5.27)	(1.21)

Standard deviations presented in parenthesis. Summary statistics in Panel A based on data on all residential mortgages from Lender Processing Services (LPS) and Panel B on data on nonprime mortgages from ABS database from RADAR warehouse. For data sources in Panel C see page 8.

Table 2: Baseline Estimates of Effect of Texas Home Equity Restrictions on Mortgage Default using One-dimensional RD
(***Dependent Variable: County Level Default Rate)***

	(1) <25 miles	(2) <25 miles	(3) <50 miles	(4) <50 miles	(5) <75 miles	(6) <75 miles	(7) <100 miles	(8) <100 miles	(9) All	(10) All
Panel A: All Mortgages										
Texas	-2.594	-2.035	-0.655	-2.360**	-2.554**	-3.130**	-2.064**	-2.176**	0.082	-0.084
	(1.567)	(1.255)	(0.845)	(1.096)	(0.826)	(0.660)	(0.666)	(0.568)	(0.598)	(0.361)
Observations	310	310	568	568	828	828	1072	1072	2250	2250
N_counties	64.00	64.00	116.00	116.00	169.00	169.00	218.00	218.00	456.00	456.00
R-Sq	0.53	0.66	0.61	0.71	0.53	0.76	0.61	0.77	0.47	0.70
Panel B: Nonprime Mortgages										
Texas	-6.425*	-2.623	-4.499**	-6.897**	-6.847**	-8.134**	-5.618**	-6.676**	-1.249	-1.364*
	(3.501)	(2.421)	(1.881)	(2.312)	(1.380)	(1.245)	(1.230)	(1.123)	(1.059)	(0.765)
Observations	310	310	569	569	829	829	1073	1073	2252	2252
N_counties	64	64	117	117	170	170	219	219	457	457
R-Sq	0.71	0.77	0.76	0.79	0.74	0.81	0.79	0.83	0.71	0.77
Linear in Distance	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Covariates	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

*Significant at 10% level; **Significant at 5% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and a linear RD polynomial in minimum distance to the Texas border (normalized to zero at the border). Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, and year effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Results in Panel A based on data on all residential mortgages from Lender Processing Services (LPS) and Panel B on data on nonprime mortgages from ABS database.

Table 3: Effect of Texas Home Equity Restrictions on Mortgage Default using Multidimensional RD
(***Dependent Variable: County Level Default Rate)***
(Data: LPS Data on All Mortgages Grouped to County Level)

	(1)	(2)	(3)	(4)	(5)
Distance Band at Texas Border	<25 miles	<50 miles	<75 miles	<100 miles	All
Panel A: Linear Polynomial in Latitude and Longitude					
Texas	-1.532**	-1.401**	-1.106**	-0.580*	-0.920**
	(0.357)	(0.379)	(0.409)	(0.324)	(0.213)
Panel B: Quadratic Polynomial in Latitude and Longitude					
Texas	-1.189**	-1.185**	-1.011**	-1.037**	-1.045**
	(0.311)	(0.328)	(0.356)	(0.328)	(0.257)
Panel C: Cubic Polynomial in Latitude and Longitude					
Texas	-1.339**	-1.480**	-1.421**	-1.020**	-1.167**
	(0.345)	(0.391)	(0.330)	(0.289)	(0.260)
Panel D: Polynomial in Latitude and Longitude using post-double-LASSO §					
Texas	-1.678**	-1.463**	-0.804*	-0.591*	-0.700**
	(0.447)	(0.413)	(0.429)	(0.321)	(0.207)
LASSO Selected Polynomial Terms	*X*	*X*	*None*	*X,Y, XY*	*X,Y, XY*
Observations	310	568	828	1072	2250
Counties	64	116	169	218	456
R-Square	0.8489	0.8499	0.8489	0.8718	0.8287
Other Covariates	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes

*Significant at 10% level; **Significant at 10% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and multidimensional RD polynomial in latitude and longitude. Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, share of mortgages with initial LTV was 80 percent or higher, county level log median household income, share of adjustable rate mortgage, share of cash-out refinance mortgages, and average county-level mortgage denial rate between 2000 and 2006, year effects, and state border-segment fixed effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Data on county level default rates and other mortgage characteristics on from a database on all residential mortgages from Lender Processing Services (LPS). §See Appendix B for details on LASSO selection procedure.

Table 4: Effect of Texas Home Equity Restrictions on Mortgage Default using Multidimensional RD

(***Dependent Variable: County Level Default Rate)***

(Data: ABS Data on Nonprime Mortgages Grouped to County Level)

	(1)	(2)	(3)	(4)	(5)
Distance Band at Texas Border	<25 miles	<50 miles	<75 miles	<100 miles	All
Panel A: Linear Polynomial in Latitude and Longitude					
Texas	-4.614**	-4.096**	-3.433**	-2.157**	-2.902**
	(1.161)	(0.916)	(1.022)	(0.888)	(0.747)
Panel B: Quadratic Polynomial in Latitude and Longitude					
Texas	-3.908**	-3.808**	-3.067**	-2.328**	-3.669**
	(1.217)	(0.825)	(0.910)	(0.890)	(0.830)
Panel C: Cubic Polynomial in Latitude and Longitude					
Texas	-5.609**	-4.796**	-4.620**	-3.203**	-3.472**
	(1.448)	(0.999)	(0.866)	(0.905)	(0.801)
Panel D: Polynomial in Latitude and Longitude using post-double-LASSO [§]					
Texas	-3.581**	-4.019**	-3.609**	-2.128**	-2.905**
	(1.352)	(0.896)	(1.002)	(0.846)	(0.746)
LASSO Selected Polynomial Terms	Y,Y^2	*None*	X,Y^2	X	X,Y,XY
Observations	301	555	815	1059	2231
Counties	64	117	170	219	457
R-Square	0.8971	0.8835	0.8942	0.9094	0.8733
Other Covariates	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes

*Significant at 10% level; **Significant at 5% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and multidimensional RD polynomial in latitude and longitude. Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, share of mortgages with initial CLTV was 80 percent or higher, county level log median household income, share of adjustable rate mortgage, share of cash-out refinance mortgages, and average county-level mortgage denial rate between 2000 and 2006, year effects, and state border-segment fixed effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Data on county level nonprime default rates and other mortgage characteristics are from ABS database on nonprime mortgages from CoreLogic. [§]See Appendix B for details on LASSO selection procedure.

Table 5: Effect of Texas Home Equity Restrictions on Nonprime Mortgage Default Hazard using Multidimensional RD

(Cox Proportional Hazard Model of Nonprime Mortgage Default using ABS Data)

	(1)	(2)	(3)	(4)	(5)
Distance Band at Texas Border	<25 miles	<50 miles	<75 miles	<100 miles	All
Panel A: Linear Polynomial in Latitude and Longitude					
Texas	-0.196**	-0.258**	-0.157**	-0.099**	-0.046
	(0.050)	(0.042)	(0.038)	(0.037)	(0.070)
Panel B: Quadratic Polynomial in Latitude and Longitude					
Texas	-0.128**	-0.243**	-0.148**	-0.162**	0.143
	(0.057)	(0.049)	(0.047)	(0.043)	(0.131)
Panel C: Cubic Polynomial in Latitude and Longitude					
Texas	-0.127	-0.279**	-0.210**	-0.212**	0.136
	(0.086)	(0.051)	(0.052)	(0.044)	(0.133)
Panel D: Polynomial in Latitude and Longitude using post-double-LASSO §					
Texas	-0.103	-0.252**	-0.208**	-0.207**	0.198
	(0.068)	(0.051)	(0.053)	(0.045)	(0.161)
LASSO Selected Polynomial Terms	$X,Y,Y^2, Y^3, X^2Y, Y^4,XY^3$	$X,Y,X^2, Y^3, X^2Y, XY^3,X^3Y$	$X,Y,X^2, Y^2, XY, Y^3,X^2Y, XY^2,X^2Y^2 ,X^3Y$	$X,Y, Y^2, XY, X^3,X^2Y, XY^2,X^2Y^2, X^3Y$	$X,Y,X^2, Y^2, XY, X^2Y, XY^2,Y^4,XY^3, X^2Y^2$
Observations	782769	2038693	5103812	8697085	14919360
Other Covariates	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Month Effects	Yes	Yes	Yes	Yes	Yes
Origin Year Effects	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes

*Significant at 10% level; **Significant at 10% level. Robust standard errors clustered by county in parenthesis. Results presented are from Cox proportional hazard model of nonprime mortgage default rates on the Texas dummy and multidimensional RD polynomial in latitude and longitude. Loans were followed up from origination to either default or non-default until the end of the sample period in 12/2011 for a maximum period of 153 months. All non-defaulting loans were treated as right-censored. The survival data is single spell with right-censoring. Other non-time varying covariates are: initial FICO score, dummy for initial CLTV was 80 percent or higher, dummy for adjustable rate mortgage, dummy for cash-out refinance, state border-segment fixed effects. Time-varying covariates are 1-quarter lagged log house price change (LaggedΔHPI), county unemployment rate, log of county-level median household income, average county-level mortgage denial rate between 2000 and 2006, year and month effects, and origination year effects. The coefficient on the Texas dummy should be interpreted as percent difference in mortgage default hazard on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data on nonprime mortgage default from ABS database from CoreLogic. §Selection of multidimensional RD polynomial terms is based on simple linear regressions. The LASSO-selected then were used in hazard model regressions. See Appendix B for other details on LASSO selection procedure.

Online Appendix for "Do Restrictions on Home Equity Extraction Contribute to Lower Mortgage Defaults? Evidence from a Policy Discontinuity at the Texas' Border"

Appendix A: Additional Robustness Tests

Informal test of precise manipulation of location around the Texas border

A crucial identification assumption for RD validity is that individuals with a strong test for mortgage borrowing do not precisely manipulate their location around the discontinuity threshold (the Texas border). As discussed earlier, the 1997 constitutional amendment in Texas significantly relaxed home equity borrowing restrictions by opening the door for homeowners to tap into their home equity through second mortgages or cash-out refinancing, subject to an 80 percent cap on CLTV. If individuals move in response to restrictions on home equity borrowing, then the 1997 amendment should lead to increased net outflow from neighboring states to Texas, relative to net outflows to the states other than Texas. I use IRS data on state-to-state migration of tax returns to present tentative evidence that borrowers did not manipulate their location in response to the 1997 amendment that eased access to home equity.

Table A2 shows that from 1993 to 1996, before the 1997 amendment, net outflow of tax returns from neighboring states to Texas was 0.08 percent of all non-migrant returns in these states. The outflows increased by 0.12 percentage points to 0.20 percent after the law change. On the other hand, net outflows to other states increased by an even larger amount--0.50 percentage points. This casts doubt on the hypothesis that ease of obtaining credit against home equity in Texas may have been associated with increased net migration from neighboring states to Texas.[36]

Additional Robustness Checks for County-Level Estimates

Tables A3 through A7 examine robustness of county-level estimates to additional covariates, alternative estimation sample, and nonparametric estimation methods. To get a sense of the extent to which the Texas policy may have lowered incidence of underwater mortgages, Table A3 reports linear RD regressions of share of mortgages underwater by 20 percent or more. Table A4 reports multidimensional RD estimates similar to Table 4 for nonprime mortgages but additionally controls for state-specific policy differences: whether the state requires judicial foreclosure and whether the state allows redemption. To account for any remaining differences in state-level policy that affects

[36] A more elaborate difference-in-differences specification controlling for other interstate differences in characteristics, also reveals no significant difference in net outflow into Texas relative to other states before vs. after the 1997 law change that eased borrowing against home equity. Results are available on request from the author.

housing supply, I also control for house price elasticity from Saiz (2010).[37] The estimates are statistically similar but larger in magnitude than those in Table 4. Table A5 presents traditional RD estimates using nonparametric methods in Calonico et al. (2014b) for a 50-200 mile distance band around the Texas border. Nonparametric RD estimates are implausibly large for counties within 50-miles but precision improves as more data in used.

Identification of the treatment effect using cross-border comparisons between Texas and neighboring states can be further improved by restricting the estimation sample to just contiguous border counties (Dube et al., 2010). In this case, estimation is based on stacked data consisting of all possible contiguous county pairs. In addition to other covariates used in previous county-level specifications, we can now include county-pair fixed effects. An added advantage is that contiguous counties just outside the Texas border are plausibly better controls for Texas' counties, obviating the need to use RD specifications. Confirming this expectation, Table A6 shows that the estimated impact of the Texas policy on nonprime mortgage default rates is strikingly similar across specifications without the RD polynomial in column (1) and with post-double LASSO selected RD polynomial specifications in columns (2) and (3). To keep the model simple, regressions in Table A6 control for a parsimonious set of baseline covariates similar to Table 2. Finally, Table A7 reports RD estimates of the effect of the Texas policy on mortgage default rates for even smaller distance bands on either side of the Texas border.

[37] The standard errors in Table A2 should be viewed as a lower bound as estimates have been clustered at the county level and not at the state level. The correct approach would be to cluster standard errors at the state-level house prices (Cameron and Miller, 2013; Cameron et al., 2011; Donald and Lang, 2007; Wooldridge, 2003). However, this is infeasible because the number of clusters (states) is just 5.

Table A1: Impact of Texas Home Equity Regulation on Serious Mortgage Delinquency Using State Level Data from 2007-2011

	(1) Prime	(2) Prime	(3) SubPrime	(4) SubPrime
Texas	-0.988**	-0.555**	-3.594**	-1.768**
	(0.218)	(0.249)	(0.875)	(0.641)
Initial FICO	-0.017	-0.015	-0.024	-0.033
	(0.013)	(0.011)	(0.055)	(0.042)
Lagged House Price Growth	-0.069**	-0.067**	-0.210**	-0.191**
	(0.016)	(0.015)	(0.037)	(0.024)
Unemployment Rate	0.547**	0.535**	1.497**	1.601**
	(0.082)	(0.086)	(0.238)	(0.178)
Log Median Household Income	0.764	0.230	6.969	8.716**
	(1.041)	(1.436)	(5.505)	(3.627)
Judicial		0.869**		4.505**
		(0.356)		(0.813)
Redemption		-0.112		-0.213
		(0.232)		(1.004)
Housing Elasticity		-0.259		-0.614
		(0.199)		(0.422)
Observations	255	245	255	245
R-Sq	0.66	0.70	0.63	0.78

Note: Standard errors clustered by state reported in parenthesis. Estimates based on simple linear regression of state-level subprime default rate from 2007 to 2011 on a Texas dummy and other state level covariates listed in the table. Estimates weighted by state employment. Sources: MBA data on delinquencies from Haver analytics; House price growth from FHFA; unemployment rate and median household income from BLS/LAUS; Initial FICO based on state-level average from ABS data from RADR warehouse. See the data section on page 8 for sources of data on other covariates.

Table A2: Migration of Tax Returns from/to Neighboring States (AR, LA, NM, and OK)
3-year Before and After 1997 Law Relaxing Mortgage Borrowing Restrictions
(All outflows and inflows measured as percent of non-migrant returns)

	(1)	(2)	(3)
	Before 1997 (1993-1996)	After 1997 (1998-2001)	***After minus Before***
A. Outflow			
To Texas	0.87	0.91	**0.04**
To Other States	2.72	2.75	**0.03**
Texas minus Other States	**-1.85**	**-1.84**	**0.01**
B. Inflow			
From Texas	0.79	0.71	**-0.08**
From Other States	2.98	2.51	**-0.47**
Texas minus Other States	**-2.19**	**-1.80**	**0.39**
C. Net Migration (Outflow-Inflow)			
To Texas	0.08	0.20	**0.12**
To Other States	-0.26	0.24	**0.50**
Texas minus Other States	**0.34**	**-0.04**	**-0.38**

Note: This table is based on state level IRS data on state to state-to-state migration of tax returns calculated using online tools at taxfoundation.org.

Table A3: Linear RD regressions of Share of Mortgages Underwater by 20 Percent or More

	(1) <25 miles	(2) <50 miles	(3) <75 miles	(4) <100 miles	(5) All
Texas	-6.715	-10.161*	-15.771**	-12.177**	1.629
	(12.580)	(5.034)	(4.061)	(3.122)	(2.129)
Year Effects	Yes	Yes	Yes	Yes	Yes
Linear Polynomial in Distance	Yes	Yes	Yes	Yes	Yes
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	73	139	246	351	898
N_counties	17.00	32.00	57.00	83.00	204.00
R-Sq	0.31	0.12	0.29	0.34	0.20

*Significant at 10% level; **Significant at 5% level. Robust standard errors clustered by county in parenthesis. Results presented are from linear regression of share of mortgages underwater by 20 percent or more at county-year level from 2007 to 2011 on the Texas dummy, a linear RD polynomial in minimum distance to the Texas border (normalized to zero at the border), and other county level baseline covariates: county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, and year effects. Estimates weighted by number of loans in each county-year cell. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Results are based on data on nonprime mortgages from ABS database and CoreLogic TrueLTV database available from RADAR data warehouse.

Table A4: Robustness of Multidimensional RD to Controlling for State Level Policy Variables
(***Dependent Variable: County Level Default Rate)***
(Data: ABS Data on Nonprime Mortgages Grouped to County Level)

	(1)	(2)	(3)	(4)	(5)
Distance Band at Texas Border	<25 miles	<50 miles	<75 miles	<100 miles	All
Panel A: Linear Polynomial in Latitude and Longitude					
Texas	-10.43**	-7.204**	-5.349**	-3.450**	-5.693**
	(2.38)	(1.827)	(1.894)	(1.673)	(1.310)
Panel B: Quadratic Polynomial in Latitude and Longitude					
Texas	-9.356**	-6.177**	-5.128**	-3.418*	-7.165**
	(2.739)	(2.036)	(1.798)	(1.821)	(1.509)
Panel C: Cubic Polynomial in Latitude and Longitude					
Texas	-12.41**	-9.790**	-5.450**	-5.401**	-8.740**
	(2.31)	(2.022)	(2.349)	(2.322)	(1.527)
Panel D: Polynomial in Latitude and Longitude using post-double-LASSO §					
Texas	-8.49**	-6.309**	-5.398**	-3.913**	-5.693**
	(2.26)	(1.852)	(1.780)	(1.641)	(1.310)
LASSO Selected Polynomial Terms	*None*	*None*	*X*	*None*	*X,Y*
Observations	301	555	815	1059	2231
Counties	64.	117	170	219	456
R-Square	0.8939	0.8900	0.8988	0.9061	0.8597
Other Covariates	Yes	Yes	Yes	Yes	Yes
State Policy Vars	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes

*Significant at 10% level; **Significant at 10% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and multidimensional RD polynomial in latitude and longitude. Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, share of mortgages with initial CLTV was 80 percent or higher, county level log median household income, share of adjustable rate mortgage, share of cash-out refinance mortgages, and average county-level mortgage denial rate between 2000 and 2006, year effects, and state border-segment fixed effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Data on county level nonprime default rates and other mortgage characteristics are from ABS database on nonprime mortgages from CoreLogic. §See Appendix B for details on LASSO selection procedure. State-specific policy variables included are dummies for judicial foreclosure, whether the state allows redemption, and state-level house price elasticity.

Table A5: Robust Regression Discontinuity Estimates Using CCT (2014)
(***Dependent Variable: County Level Default Rate)***
(Data: ABS Data on Nonprime Mortgages Grouped to County Level)

	(1)	(2)	(3)	(4)	(5)
	<50 miles	<100 miles	<150 miles	<200 miles	All
Conventional	-10.802	-3.879	-4.531*	-5.070***	-5.236***
	(20.301)	(2.518)	(2.185)	(1.442)	(1.144)
Bias-Corrected	-13.140	-3.338	-3.119	-4.051	-5.341
	(161.748)	(6.152)	(4.203)	(4.623)	(2.927)
Robust	-13.140	-3.338	-3.119	-4.051	-5.341
	(161.748)	(6.152)	(4.203)	(4.623)	(2.927)
kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Bandwidth	11.752	23.972	47.548	67.059	70.729

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Bootstrapped standard errors clustered by county presented in parentheses. Bandwidth selected using Imbens and Kalyanaraman (2011).

Table A6: Results Using Contiguous Border Counties Sample
(***Dependent Variable: County Level Default Rate)***
(Data: ABS Data on Nonprime Mortgages Grouped to County Level)

	(1) OLS	(2) LASSO	(3) LASSO
Texas	-3.735**	-3.346**	-3.012**
	(0.718)	(0.730)	(1.297)
Multidimensional RD	No	Yes	No
Traditional RD	No	No	Yes
Other Covariates	Yes	Yes	Yes
County Pair Effects	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes
N	637	637	637
N_counties	76	69	69
R-Sq	0.9460	0.9461	0.9460

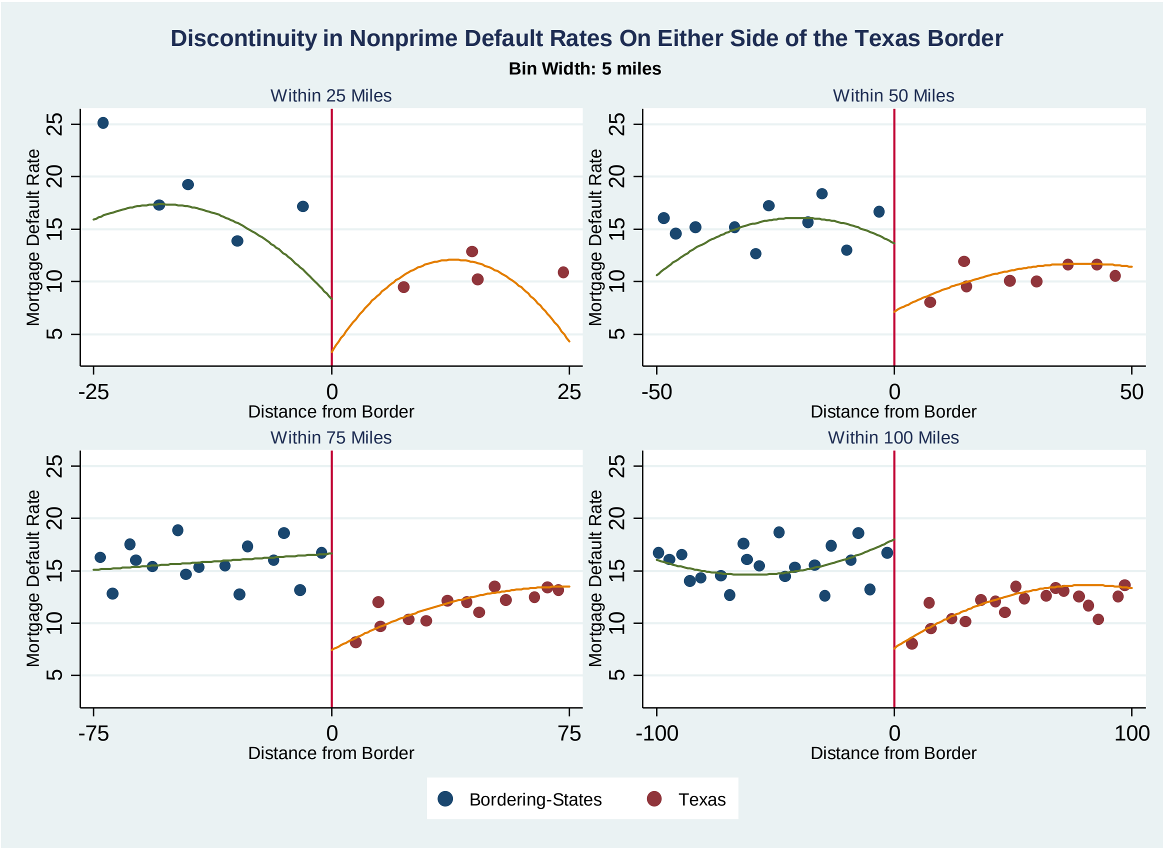
*Significant at 10% level; **Significant at 5% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and a linear RD polynomial in minimum distance to the Texas border (normalized to zero at the border). Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, county-par fixed effects, year effects. Estimation sample was restricted to contiguous border counties. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. County-level nonprime mortgage default rates are based on ABS database from RADAR data warehouse.

Table A7: RD Estimates of the Effect of the Texas Policy for Smaller Distance Bands on Either Side of the Texas Border
(***Dependent Variable: County Level Default Rate)***

	(1) <10 miles	(2) <10 miles	(3) <15 miles	(4) <15 miles	(5) <20 miles	(6) <20 miles
Panel A: All Mortgages						
Texas	-3.799**	-4.714**	-1.795**	-2.282**	-2.086*	-2.328*
	(1.158)	(1.720)	(0.823)	(0.955)	(1.180)	(1.195)
Observations	72	72	184	184	280	280
N_counties	15.00	15.00	38.00	38.00	58.00	58.00
R-Sq	0.89	0.90	0.74	0.75	0.55	0.63
Panel B: Nonprime Mortgages						
Texas	-11.031**	-10.317**	-5.932**	-3.479	-6.536**	-2.899
	(2.131)	(2.014)	(2.463)	(2.184)	(3.207)	(2.266)
Observations	72	72	184	184	280	280
N_counties	15.00	15.00	38.00	38.00	58.00	58.00
R-Sq	0.89	0.94	0.80	0.83	0.70	0.75
Linear in Distance	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Covariates	No	Yes	No	Yes	No	Yes

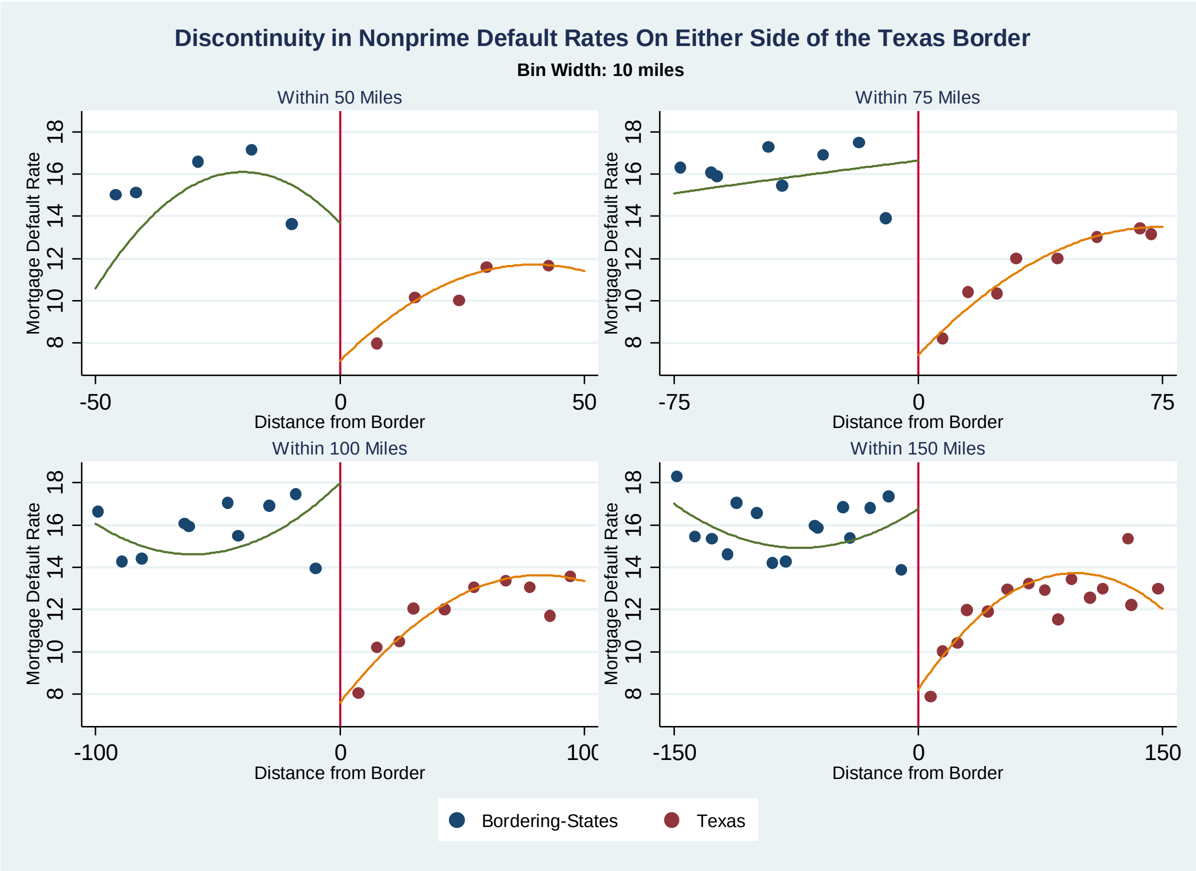
*Significant at 10% level; **Significant at 5% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and a linear RD polynomial in minimum distance to the Texas border (normalized to zero at the border). Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, and year effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Results in Panel A based on data on all residential mortgages from Lender Processing Services (LPS) and Panel B on data on nonprime mortgages from ABS database.

Figure A1



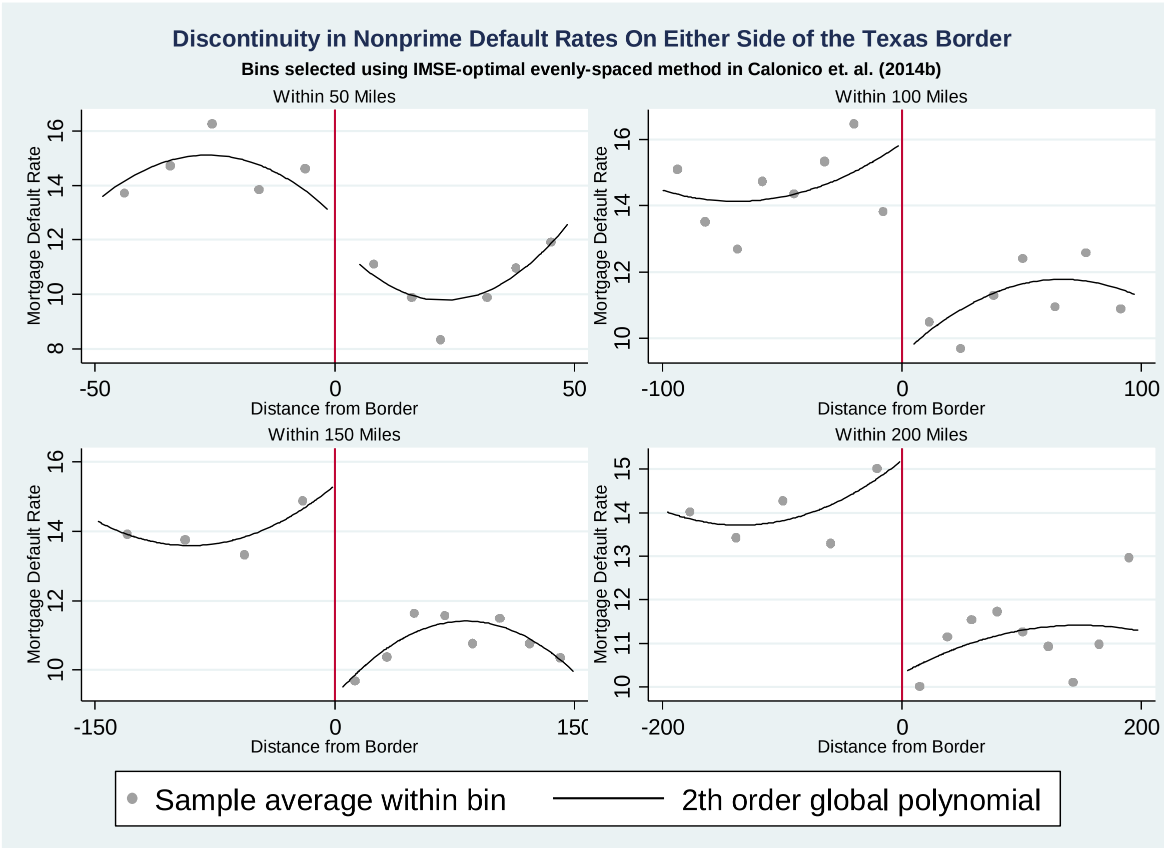
Note: The figure plots conditional mean of county-level nonprime mortgage default rate from 2007 to 2011 (controlling for baseline covariates: unemployment, initial FICO, and house price change) within 5-mile wide bins. Quadraticfitted lines are based on regression of county level mortgage default rate (residualized by subtracting the prediction from a regression of mortgage default rate on baseline covariates) from 2007 to 2011 on a quadratic polynomial in distance. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). All estimates are weighted by county-level number of nonprime loans. Data sources: County-level nonprime default rate and initial FICO calculated using ABS data from RADAR Data warehouse; county unemployment rate from BLS/LAUS; county-level house price index from CoreLogic.

Figure A2



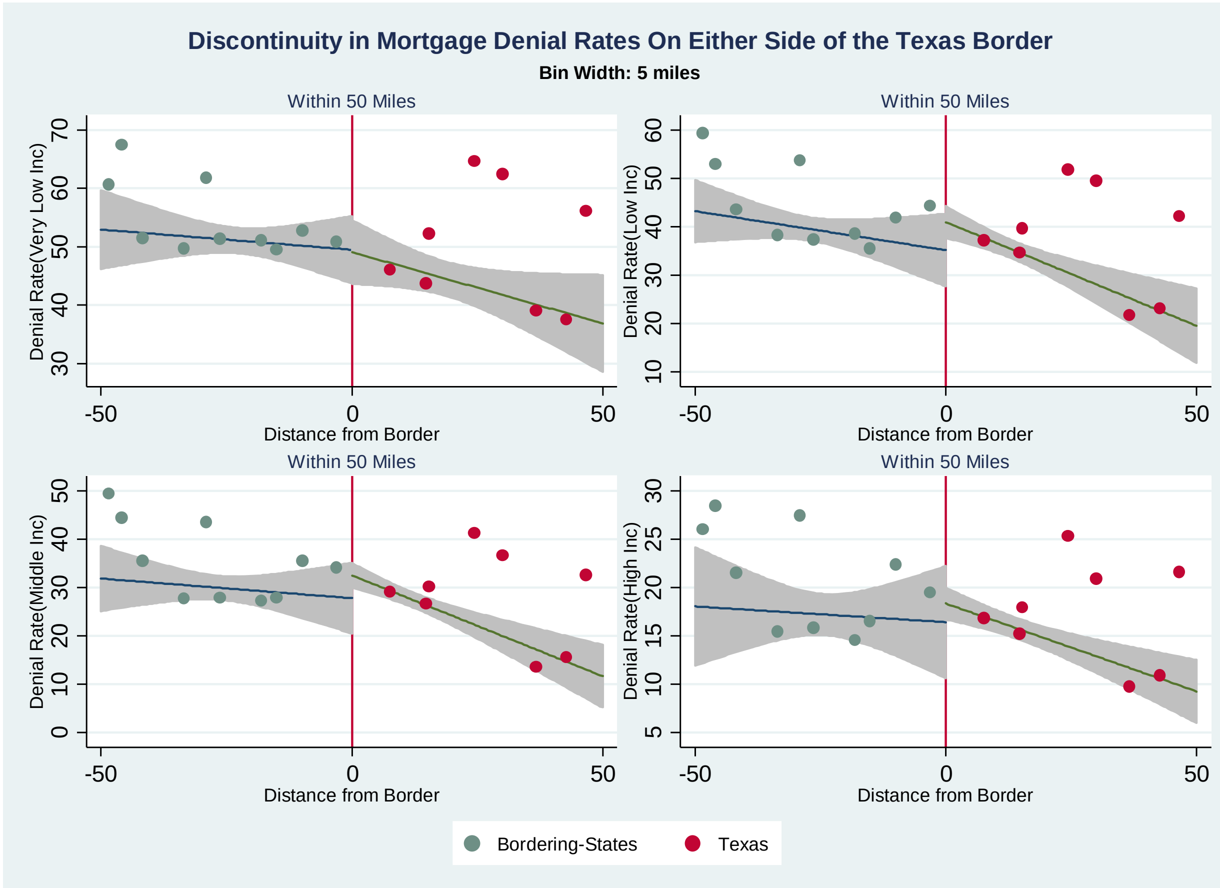
Note: The figure plots conditional mean of county-level nonprime mortgage default rate from 2007 to 2011 (controlling for baseline covariates: unemployment, initial FICO, and house price change) within 10-mile wide bins. Quadratic fitted lines are based on regression of county level mortgage default rate (residualized by subtracting the prediction from a regression of mortgage default rate on baseline covariates) from 2007 to 2011 on a quadratic polynomial in distance. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). All estimates are weighted by county-level number of nonprime loans. Data sources: County-level nonprime default rate and initial FICO calculated using ABS data from RADAR Data warehouse; county unemployment rate from BLS/LAUS; county-level house price index from CoreLogic.

Figure A3



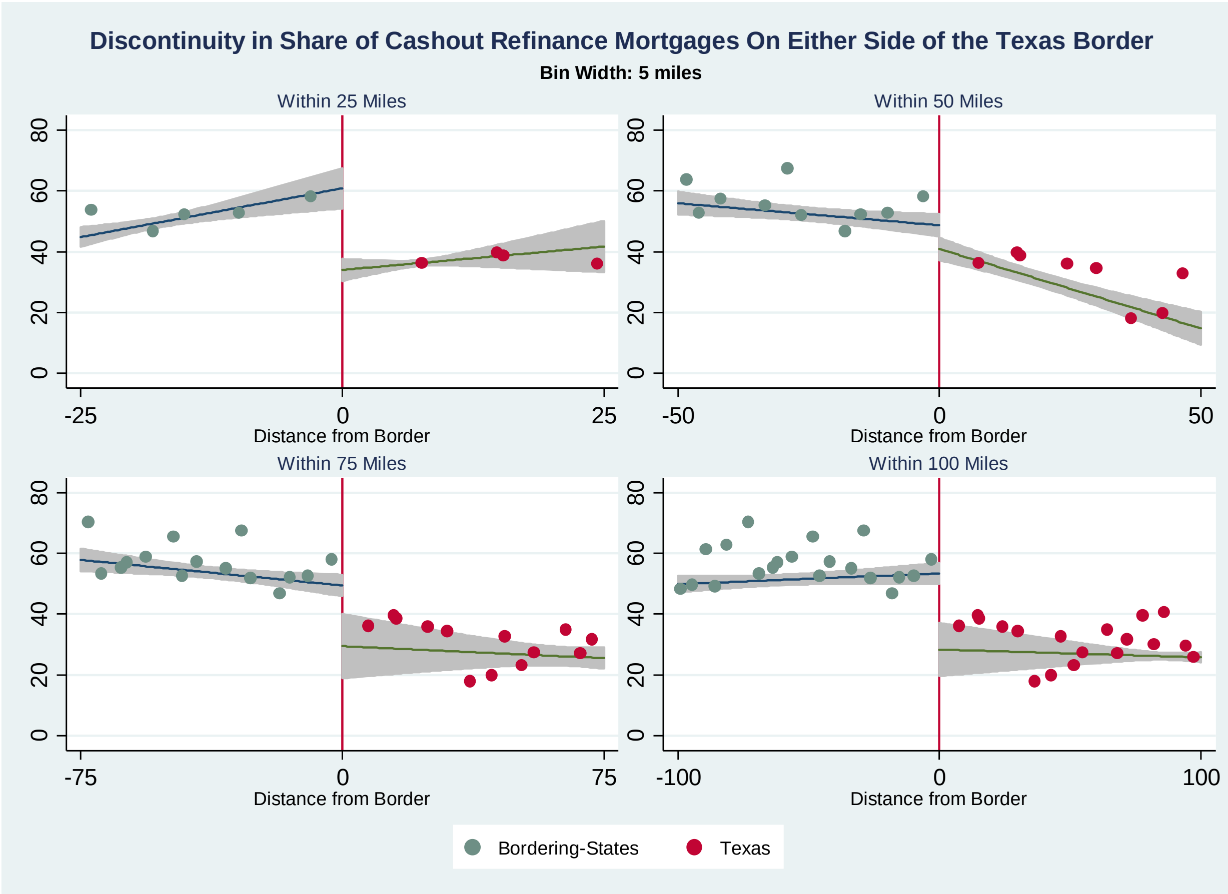
Note: The figure plots binned means of residualized county-level nonprime mortgage default rate from 2007 to 2011 (controlling for unemployment, initial FICO, and house price change) with bins selected using Calonico et al. (2014a, 2015). Quadratic fitted lines are based on regression of county level mortgage default rate (residualized by subtracting the prediction from a regression of mortgage default rate on baseline covariates) from 2007 to 2011 on a quadratic polynomial in distance. Mortgages in default are defined as those 90-plus day delinquent or in foreclosure or real estate owned (REO). Data sources: County-level nonprime default rate and initial FICO calculated using ABS data from RADAR Data warehouse; county unemployment rate from BLS/LAUS; county-level house price index from CoreLogic.

Figure A4



Note: The shaded reagion is 95 percent confidence intervals of the fitted lines. Scatterplots are of the simple unconditional mean within 5-mile binsof mortgage denial rate by income categories. Linear fitted lines are from a simple regression of the relevant variable on a linear polynomial in distance. All estimates are weighted by county-level number of nonprime loans. Data sources: Mortgage denial rates calculated using HMDA data ontained from Urban Institute.

Figure A5



Note: The shaded region is 95 percent confidence intervals of the fitted lines. Scatter plots are of simple uncodnitional mean within 5-mile bins of county level share of mortgages used for cash-out refinancing. Linear fitted lines are from a simple regression of the share of cash-out refinances on a linear polynomial in distance. All estimates are weighted by county-level number of nonprime loans. Data sources: Mortgage denial rates calculated using HMDA data obtained from Urban Institute.

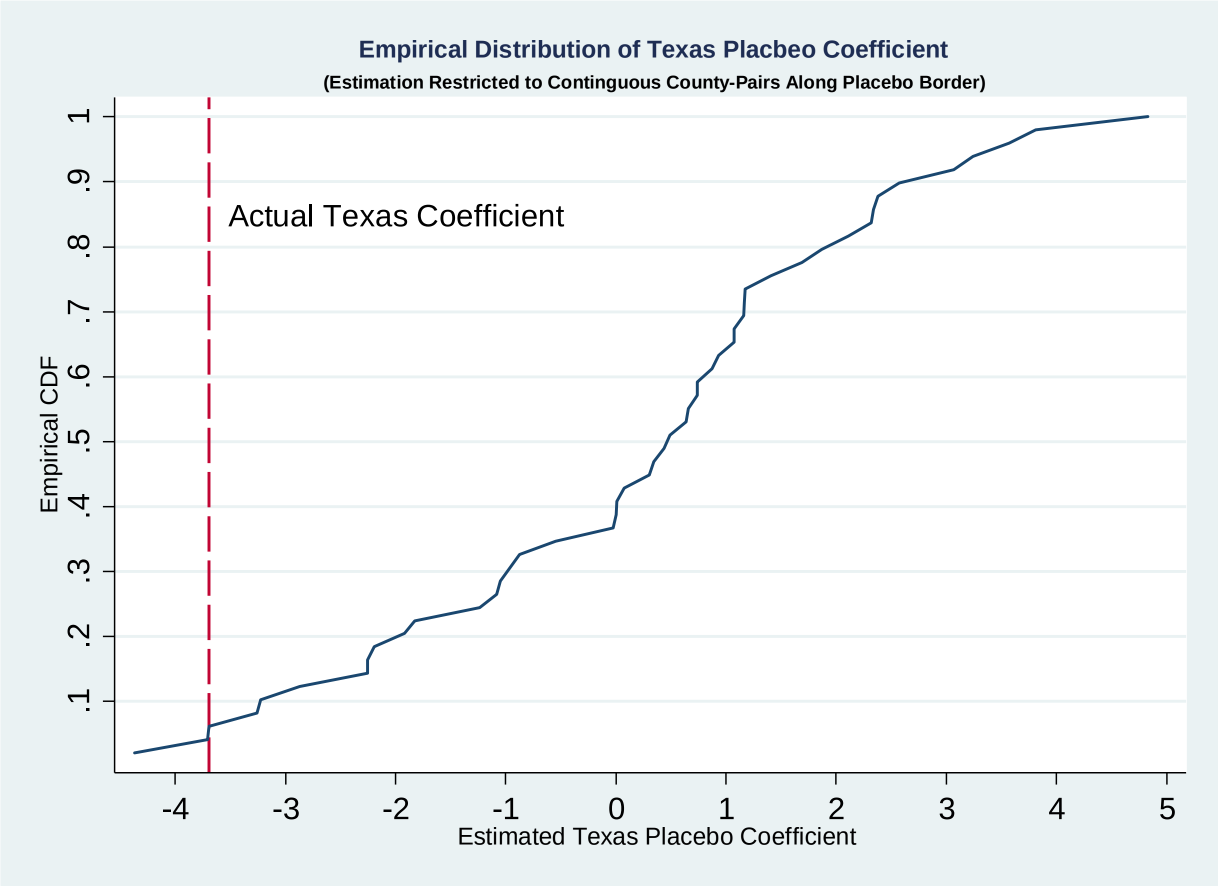
Appendix B: Placebo Tests

A central argument in the paper has been that cross-border discontinuity in nonprime mortgage default between Texas and the neighboring states exist primarily due to the Texas policy. Accounting for other state-level differences, such a large discontinuity in the nonprime mortgage default rate should not exist around the interstate borders of the remaining 47 contiguous states that allowed unrestricted access to home equity. In other words, the remaining state borders can serve as placebo borders. The estimated cross-border difference around the Texas border should then be in the lower tail of the 48 placebo estimates. The empirical CDF of the coefficient on the Texas treatment dummy can be interpreted as the p-value for the null hypothesis that the coefficient is zero.[38]

Figure B1 shows the empirical CDF of the 48 placebo estimates using just contiguous border county pairs and estimating a simple regression of the nonprime mortgage default rate on the placebo state dummy and a parsimonious set of key county-level covariates: the unemployment rate, $Lagged\Delta HPI$, and initial FICO score.[39] The Texas coefficient—plotted in the chart as a dashed vertical line—has an empirical CDF of 0.06, suggesting that the cross-border difference around the Texas border is significant at 6 percent level. To guard against the possibility that this result doesn't just apply to contiguous county pairs, I repeat this analysis for all counties within 50 miles around the borders of the 48 contiguous states for four different RD polynomial specifications in Figure B2: linear and post-double-LASSO selected polynomials in latitude and longitude (left panel) as well as analogous specifications using traditional RD in distance to the state border (right panel). All four specifications yield p-values of well below 10 percent. Overall, the placebo tests presented in Appendix B bolster the conclusion that the Texas policy indeed significantly lowered nonprime mortgage defaults.

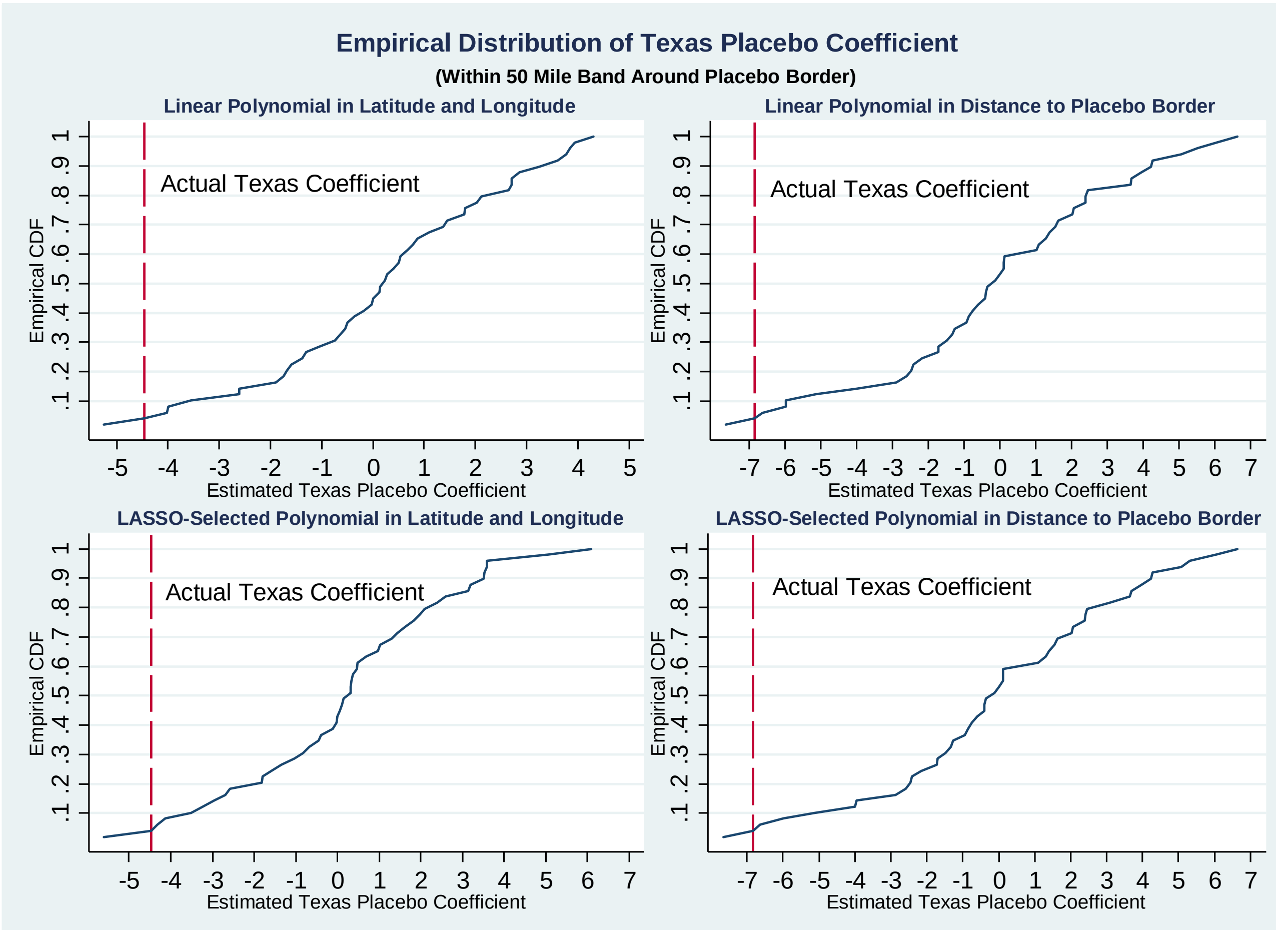
[38] See Chetty, Looney, and Kroft (2009) for a placebo test that is similar in spirit.
[39] A more parsimonious set than in Tables 4 and A5 is used due to lack of data on mortgage characteristics for all states.

Figure B1



The figure shows the empirical CDF of the 48 placebo estimates using contiguous border county pairs around the borders of the 48 contiguous states. Placebo estimates based on a simple regression of nonprime mortgage default rate on the placebo state dummy and a parsimonious set of key county-level covariates: the unemployment rate, $Lagged\Delta HPI$, initial FICO score, county-pair effects, and year effects. The Texas coefficient plotted in the chart as a dashed vertical line. The empirical CDF of the Texas coefficient can be interpreted as the p-value for the null hypothesis that the coefficient is zero.

Figure B2



The figure shows the empirical CDF of the 48 placebo estimates using RD estimation based on all counties within 50 miles around the borders of the 48 contiguous states. Placebo estimates are based on a simple regression of nonprime mortgage default rate on the placebo state dummy, the RD polynomial and a parsimonious set of key county-level covariates: the unemployment rate, LaggedΔHPI, initial FICO score, and year effects. The Texas coefficient plotted in the chart as a dashed vertical line. The empirical CDF of the Texas coefficient can be interpreted as the p-value for the null hypothesis that the coefficient is zero.

Appendix C: LASSO Specifications

To minimize bias from potentially omitting terms in the RD polynomial, the first two steps of the post-double-LASSO treatment effect estimator, consist of using LASSO to select terms in $\sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q}$ that are sufficiently correlated with the outcome variable mortgage default and the Texas treatment dummy ($Texas_s$), respectively. The union of the two sets of terms then replaces the RD polynomial in estimation of (2) and (4) in the third step. More specifically, let $\tilde{y}$ represent the residuals after partialling out all covariates from the dependent variable and the treatment dummy. LASSO uses the following penalized least squares to select the number of terms in the RD polynomial strongly correlated with each of the two variables:[40]

$$\left(\tilde{y}_{icst} - \sum_{p=0}^{P} \sum_{q=0}^{Q} \delta_{pq} X_{cs}^{p} Y_{cs}^{q}\right)^2 + \frac{\lambda}{n} \sum_{p=0}^{P} \sum_{q=0}^{Q} |\delta_{pq}| \psi_{pq} \tag{5}$$

LASSO minimizes lest square errors subject to a constraint on the sum of absolute value of coefficients. In equation (5), λ is a penalty level determining the parsimony or the number of nonzero coefficients in the model and $\psi_{pq}$are penalty loadings. A high λ selects parsimonious models by setting weakly correlated terms to zero, while a small λ yields models with large number of terms. Note that $\lambda = 0$ yields the OLS specification. I select both λ based on practical guidelines and procedures in (Belloni et al., 2014a) who suggest that a particularly good choice is:

$$\hat{\lambda} = 2.2\sqrt{n}\Phi(1 - (.1/\log(\max(k, n)))\ /(2k)), \tag{6}$$

where k is the number of number of terms in the RD polynomial, n the number of observations, and $\Phi(.)$ is the standard normal CDF. I also explore the sensitivity of estimates to different choices of λ.

Tables C1-C3 examine the sensitivity of post-double-LASSO estimates to different LASSO penalty levels $\hat{\lambda}$. The top panel repeats estimates using $\hat{\lambda}$ from Table 7 that was based on equation (6). The middle panel sets the penalty level to half of $\hat{\lambda}$. The number of terms selected in the multidimensional RD increases slightly for some distance bands, as expected, but estimates remain largely identical. The bottom panel further reduces the penalty level to just 1/5th of $\hat{\lambda}$ and shows that, although, larger number of terms is selected as penalty level is lowered, estimated impacts are highly

[40] (Belloni et al., 2014a) show that other baseline covariates can be straightforwardly included in the final step of the post-double-LASSO treatment effect estimator by partialling them out from the outcome variable and each of the set of regressors on which LASSO selection is being used, before embarking on the first two steps.

robust to changes in LASSO penalty levels. Overall, Table B1 shows that multidimensional RD estimates are not particularly sensitive to chosen penalty levels.

Table C2 is isomorphic to Table C1 and shows that multidimensional RD estimates for nonprime mortgages using post-double-LASSO to select number of terms in the RD polynomial are remarkably robust to different LASSO penalty levels $\hat{\lambda}$. Post-double-LASSO estimates with one-dimensional RD polynomial yielded results similar to baseline linear specifications presented in the bottom panel of Table 2 and are not presented due to space constraints. Finally, Table C3 shows that the post-double-LASSO estimates presented in Table A3 are robust to different LASSO penalty levels $\hat{\lambda}$.

Table C1: Robustness of Multidimensional RD with post-double-LASSO to LASSO Penalty
(***Dependent Variable: County Level Default Rate)***
(Data: LPS Data on All Mortgages Grouped to County Level)

	(1)	(2)	(3)	(4)	(5)
Distance Band at Texas Border	<25 miles	<50 miles	<75 miles	<100 miles	All
LASSO $\hat{\lambda} = 2.2\sqrt{n}\Phi(1 - (.1/\log(\max(k,n)))\ /(2k))$ §					
Texas	-1.678**	-1.463**	-0.804*	-0.591*	-0.700**
	(0.447)	(0.413)	(0.429)	(0.321)	(0.207)
LASSO Selected Polynomial Terms	*X*	*X*	*None*	*X,Y, XY*	*X,Y, XY*
LASSO $\lambda = \hat{\lambda}/2$ §					
Texas	-1.532**	-1.401**	-1.099**	-0.617**	-0.687**
	(0.357)	(0.379)	(0.394)	(0.313)	(0.251)
LASSO Selected Polynomial Terms	*X,Y*	*X,Y*	*X,Y,XY*	X,Y,XY, XY^3	X,Y,XY, X^2Y
LASSO $\lambda = \hat{\lambda}/5$ §					
Texas	-1.377**	-1.576**	-1.499**	-0.986**	-0.687**
	(0.290)	(0.373)	(0.322)	(0.312)	(0.251)
LASSO Selected Polynomial Terms	X,Y,X^2, XY^2	X,Y,XY, Y^4,XY^3	X,Y,XY, Y^4,XY^3	X,Y,XY, Y^4,XY^3	X,Y,XY, X^2Y
Observations	310	568	828	1072	2250
Counties	64	116	169	218	456
R-Square	0.8765	0.8747	0.8993	0.8853	0.8288
Other Covariates	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes

*Significant at 10% level; **Significant at 10% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and multidimensional RD polynomial in latitude and longitude. Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (Lagged∆HPI), county-level initial FICO score, share of mortgages with initial LTV was 80 percent or higher, county level log median household income, share of adjustable rate mortgage, share of cash-out refinance mortgages, and average county-level mortgage denial rate between 2000 and 2006, year effects, and state border-segment fixed effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Data on county level nonprime default rates and other mortgage characteristics are from LPS database on all residential mortgages. §LASSO penalty level λ chosen using guidelines in (Belloni et al., 2014a); see equation (6).

Table C2: Robustness of Multidimensional RD with post-double-LASSO to LASSO Penalty
(***Dependent Variable: County Level Default Rate)***
(Data: ABS Data on Nonprime Mortgages Grouped to County Level)

	(1)	(2)	(3)	(4)	(5)
Distance Band at Texas Border	<25 miles	<50 miles	<75 miles	<100 miles	All
LASSO $\hat{\lambda} = 2.2\sqrt{n}\Phi(1 - (.1/\log(\max(k,n)))\ /(2k))$ §					
Texas	-3.581**	-4.019**	-3.609**	-2.128**	-2.905**
	(1.352)	(0.896)	(1.002)	(0.846)	(0.746)
LASSO Selected Polynomial Terms	Y,Y^2	*None*	X,Y^2	X	X,Y,XY
LASSO $\lambda = \hat{\lambda}/2$ §					
Texas	-3.581**	-3.810**	-3.232**	-1.905**	-2.905**
	(1.352)	(0.830)	(0.939)	(0.896)	(0.746)
LASSO Selected Polynomial Terms	Y,Y^2	X	X,Y,Y^2	$X,Y,\ Y,\ Y^3$	$X,Y,XY,$
LASSO $\lambda = \hat{\lambda}/5$ §					
Texas	-4.420**	-4.072**	-3.629**	-2.117**	-2.905**
	(1.188)	(0.859)	(0.921)	(0.851)	(0.746)
LASSO Selected Polynomial Terms	X,Y^2,XY^3	X,Y^3,X^2Y^2	$X,Y,Y^2,$ XY	$X,Y,\ Y^3$	$X,Y,XY,$
Observations	310	569	829	1073	2252
Counties	64	117	170	219	457
R-Square	0.8977	0.8888	0.8985	0.9115	0.8733
Other Covariates	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes

*Significant at 10% level; **Significant at 10% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and multidimensional RD polynomial in latitude and longitude. Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (Lagged∆HPI), county-level initial FICO score, share of mortgages with initial CLTV was 80 percent or higher, county level log median household income, share of adjustable rate mortgage, share of cash-out refinance mortgages, and average county-level mortgage denial rate between 2000 and 2006, year effects, and state border-segment fixed effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Data on county level nonprime default rates and other mortgage characteristics are from ABS database on nonprime mortgages. §LASSO penalty level λ chosen using guidelines in (Belloni et al., 2014a); see equation (6).

Table C3: Robustness to Inclusion of State-Level Policy Variables using Multidimensional RD with post-double-LASSO

(***Dependent Variable: County Level Default Rate)***

(Data: ABS Data on Nonprime Mortgages Grouped to County Level)

	(1)	(2)	(3)	(4)	(5)
Distance Band at Texas Border	<25 miles	<50 miles	<75 miles	<100 miles	All
LASSO $\hat{\lambda} = 2.2\sqrt{n}\Phi(1-(.1/\log(\max(k,n)))\ /(2k))$ §					
Texas	-6.465**	-4.806**	-3.878**	-2.476*	-3.087**
	(2.003)	(1.499)	(1.593)	(1.331)	(1.249)
LASSO Selected Polynomial Terms	*None*	*None*	*None*	*None*	*X,Y*
LASSO $\lambda = \hat{\lambda}/2$ §					
Texas	-6.465**	-4.806**	-3.486**	-3.308**	-3.288**
	(2.003)	(1.499)	(1.743)	(1.332)	(1.300)
LASSO Selected Polynomial Terms	*None*	*None*	X,Y^2	X,X^2	X,Y,X^2
LASSO $\lambda = \hat{\lambda}/5$ §					
Texas	-6.986**	-5.282**	-3.322*	-2.986**	-4.556**
	(2.081)	(1.639)	(1.692)	(1.384)	(1.516)
LASSO Selected Polynomial Terms	X	X,X^2,XY,Y^4	X,Y,X^2,Y^2,Y^4	X,Y,X^2,Y^2,Y^4	X,Y,X^2,Y^2,XY,X^2Y
Observations	310	569	829	1073	2252
Counties	64	117	170	219	457
R-Square	0.9042	0.8980	0.9074	0.9160	0.8751
Other Covariates	Yes	Yes	Yes	Yes	Yes
State Policy Vars	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes
Border FE	Yes	Yes	Yes	Yes	Yes

*Significant at 10% level; **Significant at 10% level. Robust standard errors clustered by county in parenthesis. The dependent variable mortgage default is defined as share of mortgages 90 day+ delinquent or in foreclosure or REO. Results presented are from linear regression of county-year level mortgage default rates from 2007 to 2011 on the Texas dummy and multidimensional RD polynomial in latitude and longitude. Other county level baseline covariates included are the county unemployment rate, 1-year lagged log house price change (LaggedΔHPI), county-level initial FICO score, share of mortgages with initial CLTV was 80 percent or higher, county level log median household income, share of adjustable rate mortgage, share of cash-out refinance mortgages, and average county-level mortgage denial rate between 2000 and 2006, year effects, and state border-segment fixed effects. Estimates weighted by number of loans in each county-year cell. The coefficient on the Texas dummy should be interpreted as the discontinuity in mortgage default rate on Texas side of the border vis-a-vis NM, OK, AR, and LA side of the border. Data from (Holmes, 1998) was used to get distances of county centroid to the Texas border with respective states. Data on county level nonprime default rates and other mortgage characteristics are from ABS database on nonprime mortgages. State-specific policy variables included are dummies for judicial foreclosure, whether the state allows redemption, and state-level house price elasticity. §LASSO penalty level λ chosen using guidelines in (Belloni et al., 2014a); see equation (6).