Know Thyself: Free Credit Report and the Retail Mortgage Market [*]

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Abstract

Credit history is the top reason for mortgage rejection in the U.S. In this paper, I show that reducing consumer's cost of accessing own credit report increases mortgage demand and improves the applicant pool. Exploiting the federal extension of state laws in 2004 allowing free credit report, I document that reduced information cost leads to an increase in the mortgage demand, the mortgage approval ratio and the fraction of first-time homebuyers. The mortgages from the treated areas are less likely to default and this persists through the financial crisis. The increase in the mortgage origination and the approval ratio is not driven by lenders. Thus, I conclude that higher mortgage approval ratio is due to higher quality applicants in the market. Pool improvement occurs mainly in prime and more educated areas, and among the bottom income quartile consumers. Overall, results suggest that costly credit history information excludes some creditworthy consumers from the credit market.

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1 Introduction

The most frequent reason for mortgage rejection in the US is credit history. 29.87 million (20%) of the mortgage applications were rejected between 2000 and 2008, of which 8.34 million (28%) are rejected due to credit history.[1] At the same time, about 15% of the US population does not apply for credit for the fear of rejection.[2] I call these mismatches as Type A and Type B mismatch. Type A mismatch refers to the rejection of credit application from credit-unworthy consumers who could have saved the cost of application and rejection. Type B mismatch refers to the creditworthy consumers not applying for credit, fearing rejection. What role does the economic cost of accessing own credit history information play in the mismatch in retail mortgage market?

In this paper, I examine the link between the economic cost of accessing own credit history information and matching of consumers in the mortgage market. In a natural experiment using a difference-in-differences (DID) setup, I show that reducing the economic cost of accessing own credit history information raises the demand for mortgage and improves matching in the mortgage market. The mortgages in the treated area are less likely to default, even during and after the financial crisis. Moreover, (a) mortgages from treated areas are less likely to be rejected due to credit history; (b) consumer's tendency to credit-shop increases; and (c) the fraction of first-time homebuyers in the market increases. These effects are consistent with better *self-learning* among consumers about their true creditworthiness. The improvement in matching is observed in population with higher education, better creditworthiness, and lower income quartile. To rule out the possibility that increased mortgage approval ratio in the treated areas is driven by lenders, I show that the mortgage approval ratio in high and low lenders' density treated areas are statistically not different from each other. Also, I find no evidence of increase in private securitization in the treated areas, thus ruling out

1. If we consider only those mortgage rejections which provides reason for denial (70% of rejected applications do), the fraction of denied mortgages due to credit history jumps to 39.4% (Home Mortgage Disclosure Act, henceforth HMDA). Debt to income ratio, the second most frequent reason for rejection, affects rejection of just half as many applications as does credit history.

2. Survey of Consumer Finances (SCF) 1998, 2001, 2004 and 2007.

the securitization incentive of lenders in increasing mortgage origination. Finally, employment and wages in the non-tradable industries, a hallmark effect of credit-supply increase in an economy, do not differ in the treated areas relative to the control areas. Overall, these results highlight the role of credit reports in improving the self-learning among consumers about their creditworthiness.

Lower cost of obtaining own credit report can impact credit demand and matching in the credit market through multiple channels. First, consumers can use the information contained in the credit report prior to a credit application to better self-assess the creditworthiness. Credit report can aid in better self-assessment because it usually contains information on the consumer's credit history, and also, some indication of the available debt capacity of the consumer, as shown in the sample credit report in Figure (1). Low financial literacy and complexity of debt products act as barriers to accurate self-assessment of creditworthiness. Brown, Haughwout, Lee, and Van Der Klaauw (2011) shows that consumers underestimate their existing debt and Perry (2008) estimates that as many as 32% of consumers overestimate their credit ratings, while only 4% underestimate it.[3] Self-assessment of creditworthiness matters because incorrect self-assessment leads to worse financial outcomes (Courchane, Gailey, & Zorn, 2008). Second, accessing the credit report before applying for credit provides the consumer an opportunity to review the decision, especially if the credit report contains a credit relevant negative information.[4] Third, credit report itself may contain incorrect information. Avery, Calem, and Canner (2004) finds that in a sample of credit reports representative of the US population, about 46% (70%) of consumers had missing credit limits (in 1999 study). For these reasons, experts, including Federal Reserve Board, actively recommend consumers to check their own credit reports.[5]

3. Consumers underestimate their student (credit card) debt by as much as 25% (37%) (Brown et al., 2011).

4. The applicant can delay the application, take steps to improve the credit record, correct any inaccurate information therein, or altogether decide to not apply for credit.

5. *It can be especially helpful to see a copy of your credit report before you apply for, say a car loan, a mortgage, or a credit card. Errors in credit reports are not uncommon.* Federal Reserve Bank of Philadelphia. https://www.philadelphiafed.org/consumer-resources/publications/what-your-credit-report-says

I causally estimate the effect of reduced cost of credit history information on credit demand and matching in the credit market using changes in the regulation regarding cost of credit reports. The federal act – Fair and Accurate Credit Transactions Act (FACTA) of 2003 – grants consumers the right to obtain a *free* credit report from each of the nationwide consumer reporting agencies once every twelve months' period. However, the seven US states – Colorado, Georgia, Maine, Maryland, Massachusetts, New Jersey, and Vermont (pre-FACTA states) – had already enacted state laws prior to 2004 allowing its residents to access free credit reports (Figure 2).[6]

I utilize difference-in-differences (DID) setting in which the pre-FACTA states constitute the control group, and the states surrounding the early adopting states constitute the treatment group (Figure 3). I restrict the focus only to the counties lying along the border of control and treatment states, thereby controlling for local socioeconomic conditions (Figure 4). Moreover, this natural experiment does not rely on law enactment by individual states, but utilizes the federal extension of the existing state laws. This empirical strategy mitigates the criticism that states' selection into treatment is endogenous.

I first estimate the effect of free credit report on the number of mortgage applications. Mortgage applications in a treated census tract increase by 13.2% - 15.1%. This corresponds to \$4.83 million increase in mortgage demand per treated census tract, or \$27.7 billion in the entire treated area. Does the applicant pool improve? In the absence of a lender driven increases in credit supply, which I examine rigourously in the last section, the mortgage approval ratio captures the change in the applicant pool.[7] The mortgage approval ratio increases by 1 percentage point in the treated census tracts relative to the control census tracts. This represents ~2.7 more approved mortgages amounting to ~\$2.4 billion increase in successful mortgage origination. These results are robust to the inclusion of *Census Tract* fixed effect and "*Border* $\times$ *Year*" fixed effect

6. Colorado in 1997, Georgia in 1996, Maine in 2003, Maryland in 1992, Massachusetts in 1995, New Jersey in 1996, and Vermont in 1992. State residency for free credit report is determined by the same criteria as that for the tax residency for the state.

7. Mortgage Approval ratio is the ratio of mortgage approved or originated to total mortgages applied in a census tract.

and host of time varying controls capturing economic conditions at county and state level.

I next examine whether the increase in mortgage demand is from consumers who intend to utilize the property for occupancy, or from consumers who intend to buy properties for non-occupancy purposes such as investment in order to profit from the rising house price. Since the majority of mortgages in HMDA are for owner-occupied property (86%), it seems likely that demand increase was for occupancy purpose. To estimate the owner-occupied demand increase, I regress the number of applications and the mortgage approval ratio using the DID specification for the subset of mortgage applications which are for owner-occupied property only. The estimated increase in demand for owner occupied is 10.7%-11.5%, which is approximately same as estimated for overall demand increase. I further test for change in the fraction of total (successful) mortgages which are owner-occupied. I do not find evidence of change in fraction of not owner occupied mortgages in the application pool. Overall, these results suggest that demand increase due to free credit report was for occupancy purpose.

Now, I examine the evidence for *Self-Learning* channel of credit report through which lower cost can affect the mortgage demand and matching. First, I examine the reason for rejection of mortgage applications. If applicants are accessing credit report and taking action based on that information prior to mortgage application, a mortgage is less likely to be rejected due to credit history. I find suggestive, albeit weak, evidence of this. The fraction of application denied for credit history declines, but there is no significant change in the fraction of applications denied for debt-to-income ratio. I conduct a second test motivated by the idea that a better informed applicant is more likely to shop for a mortgage deal before the application than a less informed applicant (credit shopping). Consequently, the former is less likely to withdraw an ongoing mortgage application than the latter. Data confirms this intuition. Withdrawn applications as a fraction of total applications decrease by 0.9 percentage points (~ 2.48 applications per 1000 adult), saving ~US $26.5 million saving in upfront application fees for the applicants at an average cost of USD 400 per application. In a third test, I estimate the change in the applicant pool by examining the fraction of first-time homebuyers. The information on first-time homebuyers is available only for a subset of mortgages which are sold to Fannie Mae and Freddie Mac (Government Sponsored Entities or GSEs). In this sample, I find that the fraction of first-time buyers increases in the treated areas by 1 percentage point. This result is consistent with the view that a fraction of creditworthy borrowers enter the mortgage market after more informed about their credit history (demand suppression by creditworthy borrowers for fear of rejection under the high cost of credit history information, the Type B mismatch). Overall, these three results support the *Self-Learning* channel.

Which consumers are more likely to utilize the easier access to credit report? I conduct four tests towards this end. The first test is inspired by the intuition that it is more likely that areas with a higher fraction of prime population will have consumers discovering that they are creditworthy than areas with lower fraction of prime population. Using the fraction of prime population in a county in 1999, (Mian & Sufi, 2009), I find that the effects are mainly observed in the prime counties, but not in the subprime counties. The second test refines the previous test by utilizing a proxy – payday lenders – for the creditworthiness of census tracts, which are a finer geographic area than counties. The idea is based on the fact that payday lenders tend to locate in areas with high subprime population (Prager, 2009). Results reveal that mortgage applications increase in areas having high as well as low creditworthiness, but the mortgage approval ratio increases only in areas having high creditworthiness (identified by fewer payday establishments). The third test relies on the argument that, ceteris paribus, a more educated consumer is more likely to utilize credit report than a less educated consumer. Using the fraction of adult population with graduate or equivalent degree as a proxy for education, I find that the effects are significant in high education areas, but not in low education areas. In the fourth test, I examine the effect of free credit report across different income quartiles noting that the economic cost of mortgage rejection is higher for lower income applicant. I find that the mortgage approval ratio increases by 1 percentage point in the bottom income quartile. This suggests that the creditworthy applicants in the bottom income quartile are more likely to abstain from participating in the mortgage market when the cost of learning about own credit history is high. Overall, these four results are consistent with the changes expected from the consumers when the cost of credit report is reduced. Thus, these results also mitigate the concern that better mortgage approval ratio in the treated areas is solely due to lender driven increase in the mortgage supply.

Are these new mortgages, supposedly induced by free credit report, more likely to default? For this, I compare the default rates of the mortgages originated in the year of the event to those originated in the year before the event in the treated area relative to the control area (*Adjusted Default Rate*) over six years after the origination. Consistent with the idea that free credit report induces good quality borrowers in the market, I find that these mortgages are less likely to default, even during and after the financial crisis (2007 - 2010). This result is noteworthy. Free credit report not only resulted in more consumers applying for mortgages and lenders more likely to approving them, but also these mortgages performed better, *not worse*, than the comparable mortgages, even in and after the financial crisis.

I devote the last set of tests to examine if the increased mortgages are related to the changes in the incentive of lenders. Specifically, I address the alternative argument that these results are due to lenders increasing mortgages approvals in the pre-crisis lending boom, and not due to the changes in the pool of consumers. I begin with the observation that though lenders optimally decide the mortgage approval ratio, they do not choose the number of mortgage applications, which increases in the treated areas. Further, previous results establish that effect of free credit report is heterogeneous in characteristics of consumers – creditworthiness, income and education. In order to examine the role of lenders, I test if the effect of the experiment is heterogeneous in the characteristics of lenders. If we find that the effect is not heterogeneous in lenders' characteristics, we can infer that lender's observed characteristics is not the primary driver of the results.

First, I utilize the heterogeneity in lenders' density. This is based on the idea that if the increase in mortgage is driven by lenders, then we would expect higher mortgage origination and mortgage approval ratio in areas having high density of mortgage lenders. DID coefficients for amount of mortgage origination per adult and approval ratio in areas having high density of lenders are statistically the same as those in areas having low density of lenders. Thus, this result rules out the explanation that increased approvals are just a manifestation of lenders motivated to originate more mortgages.

Second, I examine the role of securitization in increased approval ratio. It may be argued that lenders may be originating more mortgages in a bid to earn higher commission from private securitization. If this were the true reason behind the observed increase in approval ratio in the treated areas, then we would expect that higher fraction of mortgages were sold to non-government mortgage securitizing entities. The regression results reveal the opposite. The fraction of mortgage applications which is approved and sold to the four government agencies – Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac – increases, but there is no change in the fraction of mortgages that is approved and sold to non-government entities. Thus, we can conclude that private securitization incentive of lenders is not driving the observed increase in mortgage approvals.

Third, I test the subprime supply hypothesis that the increase in mortgage approval ratio is due to lenders increasing supply in the subprime areas (Mian & Sufi, 2009). Previously, I showed that the effect of free credit report is pronounced in the prime counties and among the prime population, identified by presence of payday lenders. In a further test, I use the subset of mortgages for which the application level credit score is available from the GSEs. I define an applicant as prime if credit score is more than 620. This application level test confirms that the mortgage origination to prime borrowers increases in the treated areas, thereby rejects the subprime supply hypothesis.

Finally, I examine the role of increase in supply of credit to overall local economy. Di Maggio and Kermani (2017) isolates the effect of increase in supply of credit in a county, and shows that this leads to increase in employment in non-tradable sectors. Such credit supply induced increase in employment in non-tradable sectors may in turn stimulate higher demand for mortgage credit. Under this explanation, the increase in mortgage demand in treated areas is not due to the access to free credit report, but due to the increase in credit supply to non-mortgage related industries. To test this explanation, I examine the change in employment in non-tradable sector following the methodology of Di Maggio and Kermani (2017); Mian and Sufi (2014). I find no evidence of increase in employment and wages in the non-tradable sector in the treated areas relative to the control areas. Hence, this finding is inconsistent with the explanation of increased credit supply to local economy stimulating the mortgage demand.

All in all, the four tests examining the role of lender's characteristics and incentives support the fact that the increased mortgage demand and the mortgage approval ratio in the treated areas are not solely driven by lenders.

Related Literature

This paper contributes to the multiple strands of the literature. The most relevant is the nascent literature on information provision and its effect on market participants. This is the first paper to document that matching in the credit market can be improved if the cost of information about consumer's own credit history is reduced. In a field experiment, Homonoff, O'Brien, and Sussman (2019) finds that borrowers who are randomly provided information about their own FICO® scores are less likely to default. Kulkarni, Truffa, and Iberti (2018) show that standardized financial contract reduces consumer delinquency by 40% and sophisticated (unsophisticated) borrowers are helped the most by increased product disclosure (product standardization). Liberman, Neilson, Opazo, and Zimmerman (2018) documents aggregate welfare loss and a reduction (increase) in the cost of credit for poorer defaulter (non-defaulters) when Consumer Reporting Agency (CRAs) are barred from reporting consumer defaults to lenders. Dobbie, Goldsmith-Pinkham, Mahoney, and Song (2016) shows that removal of bankruptcy flag from credit report results in a significant increase in credit card balance and mortgage borrowing. In the investment market, consumers become more sensitive to expense ratios and short term performance after regulation makes the fee and performance disclosure of 401(k) plans mandatory Kronlund, Pool, Sialm, and Stefanescu (2019).

This paper also contributes to the literature on financial literacy and household behavior. Low financial literacy has been shown to have detrimental economic outcomes: high mortgage delinquency and home foreclosure (Gerardi, Goette, & Meier, 2010); poor mortgage choice (Moore, 2003) and large debt accumulation (Lusardi & Tufano, 2009; Stango & Zinman, 2009). Perry (2008) reports that about one-third of the population overestimates its own credit rating, while Courchane et al. (2008) shows that inaccurate assessment leads to higher financing charges and higher probability of denial. Using field experiment, Balakina, Balasubramaniam, Dimri, and Sane (2020) show that an educational intervention reduces the likelihood of borrowers purchasing a sub-optimal financial product. In a field experiment, Hundtofte (2017) shows that even though distressed borrowers increase repayments in response to loan modification programs, they ultimately fail to realize the financial benefit of the loan modification, due to imperfect financial sophistication and misvaluation of the contract. In this paper, I document that free credit report results in more consumers applying for mortgages, and higher probability of mortgage approval.

Furthermore, this paper relates to the extensive literature on the mortgage expansion in the US prior to the great recession. Literature has advanced several supply side arguments for excessive mortgage expansion. Mian and Sufi (2009) argues that subprime borrowers had disproportionately large credit growth but lower income growth, and eventually suffered large mortgage delinquencies. Adelino, Schoar, and Severino (2016); Foote, Loewenstein, and Willen (2016) and Conklin, Frame, Gerardi, and Liu (2018) document contradictory result. Keys, Mukherjee, Seru, and Vig (2010) shows that the originate-to-distribute model of securitization resulted in lenders relaxing the borrower screening. In this paper, I document the increase in mortgage applications and the mortgage approval ratio due to free credit report, which is suggestive of the demand side channel of self-learning.

Finally, this research also speaks to the nascent literature on the issues related to the information contained in credit reports. A few reports by the government agencies

– Federal Reserve Board (FED) and Congressional Research Service (CRS) – and consumer advocacy groups provide perspective on issues related to credit reports: What information is contained in the credit reports? (Avery, Calem, Canner, & Bostic, 2003); Limitation of the credit report data and its consequences on credit (Avery et al., 2004); Effect of free credit report on the CRA industry (Nott & Welborn, 2003); The extent of errors in credit reports and consumer loss (Cassady & Mierzwinski, 2004; Consumer Federation of America, 2002; Golinger & Mierzwinski, 1998). In this paper, one of the motivations for the increase in demand for mortgage credit is the reduction in demand suppression by consumers incorrectly anticipating rejection.

Rest of the paper is organized as follows. Section 2 discusses the institutional background. Section 3 describes the empirical setting. Section 4 provides the description of the data used in this paper. Section 5 shows the results and provides evidence of the suggested channels for the effects of free credit report. Section 6 discusses the role of lenders in increased supply of mortgage credit and mortgage approval ratio in the treated areas and provides evidences against it; Section 7 shows the robustness tests for the results; and Section 8 concludes the paper.

2 Institutional Background

Laws Governing Consumer's Access to Credit Report in the US: Before FACTA, Fair Credit Reporting Act (FCRA) governed the consumer credit information related laws in the US. Even under FCRA, consumers have the right to see the contents of their credit report except for the credit score (Avery et al., 2003). The 1992 amendment to FCRA mandates that the cost of disclosure of credit information should be reasonable, while the 1996 amendment to FCRA sets the maximum cost at $8. Moreover, under FCRA consumers could receive a credit report without charge under specific circumstances. For example, a consumer making a request within 60 days after receiving a notice of an *adverse action* taken against him or her on the basis of the information in the credit report.[8][9]

Even though FCRA allowed free credit report at the federal level under specific circumstances to the US consumers, it was extremely uncommon for consumers to proactively request their own credit report. Out of approximately 1 billion credit reports generated annually, only 1.6% is disclosed to the consumers (Avery et al., 2004). Of these 1.6% consumer-disclosed reports, only 5.25% is proactively requested by the consumers, while 94.75% is disclosed to the consumers under the FCRA provisions mentioned earlier (Nott & Welborn, 2003).[10] Thus, only 0.084% of all credit reports generated are disclosed to consumer as a result of a request by the consumer.

In addition to the federal provisions under FCRA, residents in 7 states – Colorado (CO), Georgia (GA), Maine (ME), Maryland (MD), Massachusetts (MA), New Jersey (NJ), and Vermont (VT) – could access free credit report under respective state laws enacted over the years (see Footnote 6). The key provisions of FCRA were to expire in 2003, leading to the enactment of Fair and Accurate Credit Transactions Act (FACTA) on December 4, 2003. Being a federal law, FACTA allows US consumers to utilize free credit report annually. Thus, the residents in pre-FACTA states can enjoy free credit report under respective state laws as well as under the FACTA.

3 Empirical Setting

Seven pre-FACTA states (CO, GA, ME, MD, MA, NJ and VT) had free credit reports available for its residents prior to 2005 (see Footnote 6 and Figure 2); while all the

8. Adverse action notice can be sent to a consumer by the *user* of consumer report (e.g. banks, financial institutions, insurance firms), or, a debt collection agency affiliated with the CRA stating that the consumer's credit rating may be or has been adversely affected.

9. Furthermore, consumers can receive credit report free of charge once in 12 months if he or she makes a request to the CRA for the credit report and certifies that: (A) She/he is unemployed and intends to apply for employment in the 60 day period beginning on the date on which the certification is made; (B) She/he is a recipient of public welfare assistance; (C) She/he has reason to believe that the file on the consumer at the agency contains inaccurate information due to fraud.

10. Break up of the 94.75% credit reports disclosed under FCRA provisions is: 84% due to *adverse action*; 11.5% due to fraud claim; 0.4% due to unemployment, 0.1% due to consumer being on public assistance.

US states got access to free credit report after the enactment of FACTA in 2004, and subsequent establishment of www.annualcreditreport.com in 2005.[11] To evaluate the effect of free credit report, I designate the seven pre-FACTA states as a control group, and the states bordering these pre-FACTA states as the treatment group in a difference-in-differences (DID) setting. Figure 3 illustrates the control and the treatment states on the US map.

To isolate the treatment effect of free credit reports from the effect of local economic conditions, I restrict the focus over narrow geographic area around the borders of pre-FACTA states. I do this by focusing only on the counties lying at the border of pre-FACTA control states and surrounding treatment states, and removing the inner counties of treatment and control states (*border county strategy*). Figure 4 illustrates this strategy. For example, the Garrett County, Maryland (a border county from control state) and Somerset County, Pennsylvania (a border county from treatment state) will be included in the sample, while inner counties of Maryland (e.g. Howard county) and Pennsylvania (e.g. Montgomery) will be excluded.

The main regressions specification is as follows:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it} \tag{1}$$

where y_{ijct} is the outcome variable for a census tract level i from a county c lying at the border of control state j in year t. Recall that there are seven control states, hence j ranges from one to seven. Key outcome variables of interest are the number of mortgage applications aggregated over census tract, mortgage approval ratio in a census tract, percentage of application withdrawal, and denial rate of applications due to

11. www.annualcreditreport.com was rolled-out in four phases from Dec 2004 to Jan 2005:
Dec 1, 2004: Alaska, Arizona, California, Colorado, Hawaii, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, and Wyoming.
Jan 3, 2005: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.
Jan 6, 2005: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, Oklahoma, South Carolina, Tennessee, and Texas.
Jan 9, 2005: Connecticut, Delaware, DC, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, Vermont, Virginia, and West Virginia.

credit history. $Post_T$ takes value 1 for year $t \geq 2005$.[12] $Treatment_{ic}$ is 0 for all the census tracts i in counties c which are at the border of pre-FACTA (control) states; it is 1 for all the census tracts i in counties c at the border of the treatment states. α_i controls for time invariant and census tract specific fixed effects. $Economic\_controls$ are county and state level annual variables capturing the fluctuations in the local economic conditions. Variables included in $Economic\_controls$ are the annual growth rate of income per capita in the county, aggregate establishments in the county, aggregate annual payroll in the county, aggregate employment in the county, and the annual growth rate of gross domestic product (GDP) of the state. $\gamma_{j,t}$ is "$Border \times Year$" fixed effect. It groups together all the census tracts i which lie around the border of the same control state j. It ensures that the census tracts in a control county of a pre-FACTA state, say Colorado (state j), is compared only with the census tracts from the treatment counties *surrounding* Colorado. This means that a control census tract from Colorado does not get compared with treatment census tract from states surrounding Georgia.[13] Further, it controls for any time-varying regional economic shock affecting neighboring states. I cluster the standard errors at the county level in all specifications to account for any potential correlation in error terms from census tracts belonging to same the county, and also to account for any serial correlation in the dependent variable.

This empirical strategy critically relies on the fact that residents in the seven pre-FACTA states accessed free credit report significantly more than the bordering treatment states prior to 2005. Data on free credit report usage prior to 2004 confirms this assertion. In the Senate Hearing on FCRA, Senator Bennett reported that the use of free credit report, relative to the national average, was 250% higher in GA, 204% higher in

12. Though the act was passed in Dec 2003, the centralized source for free credit report was first rolled out on Dec 1, 2004. Since all four phases were rolled out from Dec 1, 2004 to 9 Jan 2005, I use 2005 as the event year.

13. The sample consists of 7 control states and 20 adjacent states. To account for local time varying economic shock, I employ "$Border \times Year$" fixed effect. Here, a border is identified in terms of the control state. For example, the border fixed effect identifier for the control state Colorado, will take same value for all the states sharing border with Colorado, namely — WY, UT, AZ, NM, OK, KS, and NE.

MD, 153% (458%)[14] higher in CO, 35% higher in NJ, and 25% higher in MA.[15] Moreover, some evidences suggest that the pre-FACTA states have better credit environment than the states with no free credit report. Vermont, in 2002, had the lowest rate of consumer bankruptcies in the US; Massachusetts the second lowest. Similarly, the effective interest rate on a conventional mortgage in Vermont and Massachusetts are below the country median.[16]

Another advantage of this empirical setting is that it does not use the state-by-state adoption of free credit report laws, which may be an endogenous action of the state in response to prevailing socio-economic local conditions.[17] Hence, this empirical setting mitigates the endogeneity concern that some state specific observed or unobserved characteristics are driving the enactment of the law and the outcomes of interest.

4 Data

The key data used in this paper is the US mortgage data available under the Home Mortgage Disclosure Act of 1975 (HMDA). HMDA data provides application level detail on applicant's demographics (race and gender), income, loan amount; type of the financial institution handling the mortgage application, outcome of the application, and geographic location of the property at the census tract level. The time period for the study is from 2000 to 2008. I use the data until 2008 to allow for sufficient post experiment observations, since the experiment occurs at the beginning of 2005. The sample includes mortgages for all the three purposes – home purchase, refinance, and

14. Based on free credit report usage rate data from Nott and Welborn (2003) and national average usage rate data from Senate Hearings (see Footnote 15)

15. Hearings before the committee on Banking, Housing, and Urban Affairs United States Senate. S. HRG. 108–579.

16. Prepared Statement of Joel R. Reidenberg. Hearings before the committee on Banking, Housing, and Urban Affairs United States Senate. S. HRG. 108–579.

17. Consider the case of Vermont. In 1991, Experian (then, TRW Inc.) erroneously garbled the credit report of every citizen residing in Norwich claiming that everyone has failed to pay property taxes. This could have resulted in banks or other lenders rejecting these residents if they applied for new credit. TRW settled the subsequent state lawsuit in 1992 and paid compensation to each affected homeowner. Vermont responded with the 1992 legislation mandating free annual credit report for every requesting state resident.

home improvement.[18]

The coverage of mortgages in the US under HMDA is the largest. It contains 190.3 million application level observations over the sample period. I start processing this data by first removing the observations for which state, county, or census tract information is missing or "NA", or state FIPS is "0", "00" or "0 ". This drops 2.5% of the observations, leaving 185.6 million mortgages with identifiable county. Next, I drop three types of mortgages. First, I drop covered loan purchases by the financial institution from other institution (18.80%), as these mortgages are not borrower initiated transactions. Second, I drop the pre-approval request denied by financial institution (0.01%) as this data has been included in HMDA reporting only from 2004. Third, I drop the pre-approval request approved by the financial institution but not accepted by the applicant as this data too has been included in HMDA only since 2004, and also as this is an optional reporting (0.025%). This leaves 150.7 million mortgage applications in the sample. I aggregate these mortgages at the census tract and year level, yielding 65,976 unique census tracts, and 572,512 $Census\ Tract \times year$ observations. Utilizing the *county adjacency* data,[19] I select the census tracts which lie in the counties at the border of the control and treatment states (see Figure 4). These census tracts constitute the final sample of 9,821 unique census tracts – 5,724 in the treatment group and 4,097 in the control group – making up 83,236 "$Census\ Tract \times Year$" level observations.

Though the coverage of HMDA data is the largest, it does not provide some important mortgage level details such as the credit score of the applicant. Hence, for some tests which require these variables I utilize the data from the Government Sponsored Agencies (GSEs) – the Federal National Mortgage Agency (Fannie) and the Federal National Home Loan Mortgage Corporation (Freddie). GSEs provide data on 30-year fixed rate single family mortgages purchased by them. This mortgage Type As the

18. HMDA uses census tract definition from Census 1990 for data until 2002, and from Census 2000 for 2003 onwards. To make the geographic area consistent over this regime switch, I map the Census 1990 tract definition to Census 2000 tract using the population scale data provided by Census Bureau (2006).

19. US Census Bureau provides data on which counties are surrounded by which other counties. https://www.census.gov/geographies/reference-files/2010/geo/county-adjacency.html

most popular mortgage Type An the US. The combined data, henceforth the GSE data, has 33 million mortgage level observations.[20] The data consists of application level information on debt to income ratio, credit score, first-time homebuyer flag, investment purpose and more. The property location is available at the 3-digit zip code (henceforth, zip3) and state. To map zip3 locations to the counties at the border of the states, I use the 2010 Q3 version crosswalk files provided by the US Department of Housing.[21] I aggregate the mortgage level observations to zip3-state level. This creates a panel of 225 unique zip3-states leading to 7,711 "$Zip3 - state \times Quarter$" observations.

I use a few other data sources in this paper. For gauging the creditworthiness of a county, I use Federal Reserve Bank of New York and Equifax (n.d.) data on subprime county population. For measuring county level economic characteristics such as employment and number of establishments, I use data from the annual County Business Patterns survey.[22] To map the zip code level variables from County Business Patterns to census tract level, I use the Geocorr 2000 tool from the Missouri Census Data Center.[23] The data on state level economic conditions comes from the Bureau of Economic Analysis, and the data on population characteristics at census tract level is from Census 2000 (Manson, Schroeder, Van Riper, & Ruggles, 2019).

Key variables of interest are the number of mortgage applications; the mortgage approval ratio; the fraction of total applications which are denied for credit history or debt to incomereason; and the fraction of applications withdrawn by the applicants. I define an application to be successful if the mortgage has been either originated or the

20. The data from Fannie Mae's consist of 30-year, fixed-rate, fully documented, single-family amortizing loans that the company owned or guaranteed on or after January 1, 2000. The data from Freddie Mac consists of fully amortizing 30-year fixed-rate, Single Family mortgages, that the company acquired with origination dates from 1999 onward.

21. Since Zip3 borders do not align perfectly with the county borders, I first aggregate the GSE mortgage data up to the zip3-state level, and then scale it down to the county level using a scaling factor. The scaling factor is the ratio of population living in a border county to the combined population living in all possible counties encompassed by a zip3-state geographic area. URL for crosswalk data is: `https://www.huduser.gov/portal/datasets/usps_crosswalk.html`

22. County Business Patterns data is available at the URL: `https://www.census.gov/programs-surveys/cbp/data.html`

23. *Geocorr 2000: Geographic Correspondence Engine. Version 1.3.3 (August, 2010) with Census 2000 Geography*. `http://mcdc.missouri.edu/applications/geocorr2000.html`.

application has been approved but not accepted by the applicant. Mortgage approval ratio is the ratio of the number of successful applications to the number of total applications in a census tract. Other four ratios are also calculated as a fraction of total applications in a given census tract.

Table 1 provides the summary statics of the HMDA sample. Panel A shows the summary statistics for the entire sample while panel B shows the statistics for the pre-treatment sample. We see that the treated census tracts have fewer mortgage applications per 1000 adult, lower mortgage approval ratio, and higher fraction of applications denied due to credit history and denied due to debt to income ratio. The five ratios – the approval ratio, the three denial ratios, and the withdrawal ratio – do not sum to one. There are two reasons for this. First, reporting of denial reason is not mandatory under HMDA regulations, hence an application may be recorded as denied without any stated reason (70.81% of the denied applications have at least one stated denial reason). Second, an application can have multiple reasons for denial, e.g. denied for credit history and debt to income ratio.

Panel B shows a comparison of the treatment and control groups in the pre-treatment period. We see that the differences between treatment and control census tracts in the pre-treatment sample are similar to those observed in the full sample in Panel A. The p-value for the t-test of mean between the two groups for each variable is also shown in Panel B. Results from the t-test suggest that control and treatment census tracts are different in pre-treatment years on these observed characteristics. This also raises the endogeneity concern that these groups may differ on unobservable characteristics. This concern can be mitigated in two ways. First, difference-in-differences setting can accommodate pre-existing differences between the treatment and the control subjects. Second, the visual representation in Figure 5 seems to suggest the parallel trend. The difference in the mortgage approval ratio starts to increase after the experiment. Third, in all regressions I include *Census Tract* fixed effects accounting for any time invariant differences across the census tracts. I also include "*Border* $\times$ *Year*" fixed effects. This can control flexibly for any time varying regional shock that impacts neighboring states.

One may argue that establishment of FACTA in Dec 2003, and subsequent establishment of www.annualcreditreport.com is not a significant event, thus the natural experiment is invalid. I address this concern in two ways. First, I plot the search interest for the keyword *Free Credit Report* in Figure 6 from 2004 to 2010.[24] Search interest shows a significant peak in Jan 2005, when the website was established, suggesting that there was significant consumer interest in free credit reports in 2005.

Second, I show in Figure 7 that the popularity of the keyword *Free Credit Report* increased significantly in the treatment states after the event, but there was no difference in popularity before the event. To do this, I begin by sourcing the *Interest by subregion* data from Google Trends for the keyword *Free Credit Report* for each year from 2004 to 2008. I calculate the mean of the popularity rank for the treatment and the control states in each year.[25] I calculate $Popularity_{trt} - Popularity_{ctrl}$ for each year, the resulting plot for which is shown in Figure 7. The plot suggests that the keyword *Free Credit Report* was equally popular in both the treatment and control states in pre-event year 2004, but the treatment states became more popular after 2005, the experiment year.[26]

5 Results

In this section, I provide the empirical results of the study. I first provide the baseline results, then present the results highlighting the plausible channels. Then, I show the

24. Search interest numbers are standardized index representing search interest at any time relative to the highest point during the time period of the analysis, over a given region(US in the present case). A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term. Since Google Trends data starts from January 2004, past data is not available.

25. Google calculates the *Popularity* of a region on a scale from 0 to 100. Value of 100 represents the location with the highest popularity of the search term as a fraction of total searches in that location. A value of 50 indicates a location which is half as popular. A value of 0 indicates a location where there was not enough data for the search term.

26. It is important to note that the methodology Google uses to calculate the popularity of a keyword in a region implies that increase in popularity of one area would mechanically reduce the popularity in other areas. Also, we cannot interpret how much the popularity increased over the year, as the popularity rank is re-based to 100 and is assigned to the region where the keyword is most popular, every year.

results highlighting the heterogeneous effect of free credit report across different characteristics of consumers. At the end, I discuss the performance of the mortgages in the treated areas after the advent of free credit report.

Baseline Results

The baseline results are obtained using regression Equation (1). The outcome variables of interest are the number of applications per 1000 adult population and the mortgage approval ratio, each calculated at census tract level. All specifications use *Census Tract* fixed effects and "*Border* $\times$ *Year*" fixed effects. As discussed earlier, *Census Tract* fixed effects control for any pre-existing difference across different census tracts. "*Border* $\times$ *Year*" fixed effects serves two purposes. First, it controls for any shock that might affect different regions of the US at a different time, e.g. a shock affecting Colorado and surrounding states in the year 2003. Second, it ensures that the census tracts in a control county of a pre-FACTA state, say Colorado, is compared only with census tracts from treatment counties *surrounding* Colorado, and it does not get compared with treatment county surrounding any other pre-FACTA states, say Georgia.

Table 2 shows the results for baseline regression. Column (1) and (2) shows the regression of total applications per 1000 adult population as the dependent variable. The coefficient of interest is "*Treat* $\times$ *Post*". It captures the change in number of mortgage applications in treatment counties relative to control counties after the free credit report becomes available in the treatment counties. In column 2, the economic controls (county level annual growth rates of income per capita, aggregate establishments, aggregate annual payroll, aggregate employment, and state level growth rate of GDP) are added. We see that a treatment census tracts see an increase of 11.61 - 13.52 mortgage applications per 1000 adult. This is 11.6% - 13.5% increase in mortgage applications (over the pre-treatment average of 100.56 in treated census tracts). Average mortgage size in the treatment counties in pre-treatment period is ~$155,500. Thus, the consumers demand for mortgage increased by $1.8 million per 1000 adult, by $4.83 million per treated census tract, or, by $27.7 billion in the entire treated area after free credit report becomes available.

Coefficients "$Treat \times Post$" in Column (3) and (4) estimate the effect of free credit report on the change in the mortgage approval ratio. The mortgage approval ratio increases by 1% in the treatment counties after free credit report becomes available. This increase represents ~2.7 more successful application per treated tract, 15,454 more successful applications in the entire treated area, or ~$2.4 billion increase in successful mortgage origination across all treated census tracts. In the absence of supply side effect, which I show later in Section 6, we can interpret the increase in the mortgage approval ratio as the improvement in the borrower pool.

Next, I examine whether the observed increase in the mortgage demand and the mortgage approval ratio is utilized to finance properties for occupancy purpose, as opposed to investment purpose. For this, I re-estimate the baseline regression for only the owner-occupied mortgages. Panel A of Table (3) shows the result. The estimates are broadly similar to the baseline specification. Mortgage applications increase by 10 - 12% and the mortgage approval ratio increases by 1 percentage point in the treated areas relative to the control areas. Further, I examine if the composition of mortgage applications and successful mortgages changes between owner-occupied and not owner-occupied. For this I regress fraction of total (successful) mortgages which are non owner-occupied. Panel B of Table (3) shows the results. Column (1) and (2) shows that there is no change in the fraction of mortgage applications that are not for occupancy purpose. Column (3) and (4) shows that there is very weak evidence of increase in the fraction of not owner-occupied mortgages by 1 percentage point for successful applications. Nonetheless, about 86% of the mortgages in the HMDA sample are for occupancy purpose. Hence, the 1 percentage point increase in fraction of non-occupancy mortgage is economically small. Thus, we can conclude that free credit report leads to mostly occupancy related demand increase.

Channel

I now examine three mechanisms of *Self Learning* through which credit report can affect the demand for mortgage demand and the mortgage approval ratio – credit history improvement, credit shopping, and new borrowers.

Credit History Improvement

If applicants are more likely to access their credit report after the FACTA, then applicants are more likely to take remedial actions (if any) before applying for a mortgage. Thus, in aggregate, mortgage applications by the *credit history informed* borrowers is less likely to be denied for *credit history* reason, than for other reasons. Hence, we should see a drop in the fraction of mortgage rejection due to credit history reason, and we should not see any significant change in fraction non-credit history related mortgage rejections, say debt to income ratio.[27] I test these predictions next.

I regress the fraction of total applications denied due to credit history and debt to income ratio using Equation (1). I estimate this specification for all census tracts, and for the subgroup of census tracts for which denial rate (per 1000) are higher in the pre-event year 2004 than the *regional mean*.[28]

Table 4 shows the results. We see that the Fraction of mortgage applications denied due to credit history decreases in the treatment census tracts relative to the control census tracts, but it is significant only in areas which had high denial rates prior to the experiment. A plausible reason for the treatment effect to be significant only in the high denial areas is that we cannot estimate the reduction in denial due to a certain reason if mortgages are not likely to be denied at the first place. We also see that there is no significant change in the likelihood of a mortgage being denied due to debt to in-

27. Of the 150.7 million mortgages in HMDA over 2000-2008, 29.87 million (19.82%) are denied. Out of the total denials, 21.15 million (70.81%) mention the denial reason. Of the mortgages which mention the denial reason, the two most frequent stated reasons are: credit history (8.34 million, 39.43%) and debt to income ratio (4.05 million, 19.15%).

28. For clarity on calculation of regional mean, consider the control state Colorado (CO) and all the surrounding treatment states. Regional mean for the denial rate is the average of the denial rate across census tracts in all the counties at the border between CO and WY, UT, AZ, NM, OK, KS and NE. A census tract is then classified as "higher denial area" if its denial rate is more than the regional mean. These steps are repeated for all seven control states, thereby dividing entire sample into higher and lower denial area.

come ratio. These results, albeit weak, are suggestive of the credit history improvement mechanism.

A limitation of this test is that under HMDA regulations reporting the reason for denial is not mandatory. This limitation is not a concern for two reasons. First, even though reporting the denial reason is optional, the compliance rate is 70.81% over 2000-2008 (see Footnote 27). Second, these results are unbiased to the extent that the incentive to report denial reason is not changing for HMDA lenders across the treatment and the control census tracts precisely in 2005, which seems unlikely. Thus, free credit report seems to result in improvement in credit history.

Credit Shopping

Consumer has a right to withdraw an ongoing mortgage application. If she withdraws before the lender has made the credit decision on the application, the application is recorded as *withdrawn* in the HMDA dataset. Such withdrawals are costly for the applicants, as it results in forfeiture of the upfront fees which can be as high as US$ 400.[29] Yet on average 12% of mortgage applications are withdrawn.

Anecdotal evidences suggest that the most common reason for withdrawal is credit shopping – consumer withdraws the ongoing mortgage because she has secured a mortgage offer at better terms from another lender.[30] An applicant armed with knowledge of her own credit report is more likely to do credit shopping *before* making the mortgage application than a consumer with no knowledge of own credit report. Consequently, the former is less likely to withdraw an ongoing application than the latter. If this is true, then in aggregate, the fraction of withdrawn applications in the treatment census tracts should drop relative to the control census tracts.

Table 5 shows the result of regressing fraction of mortgage applications withdrawn

29. https://www.reddit.com/r/personalfinance/comments/38k1l5/withdrawing_a_mortgage_application/

30. Applying to multiple lenders in a short period of time is not penalized by CRAs. For example, Experian, one of the three CRA encourages applicants to credit shop. "If you're shopping for a new auto or mortgage loan or a new utility provider, the multiple inquiries are generally counted as one inquiry for a given period of time. The period of time may vary depending on the credit scoring model used, but it's typically from 14 to 45 days. This allows you to check at different lenders." https://www.equifax.com/personal/education/credit/report/understanding-hard-inquiries-on-your-credit-report/

using Equation (1). We see that the fraction of withdrawn applications drops by 0.9 percentage points in the treatment counties relative to the control counties. This represents ~2.48 fewer withdrawn applications in a census tract, or 66,174 less withdrawn applications over all treatment counties, saving applicants US $26.5 million in upfront fees.

First-time Homebuyers

A Type B mismatch in the credit market refers to the phenomenon when creditworthy applicants do not apply for credit for fear of rejection. Free credit report can reduce the extent of this mismatch by aiding the consumers in better assessing their credit worthiness. I test this claim by observing the change in fraction of the first-time homebuyers in the mortgage market after the experiment. Information on whether an applicant is a first-time homebuyer is not available in the HMDA data, so I use the combined GSE data for this test. As previously explained, GSE data is a subset of mortgages in the US consisting of 30-year fixed rate mortgages purchased by Fannie Mae and Freddie Mac only, and is available at the 3-digit zip code level. Moreover, 6.71% of the observations in this data cannot identify if the applicant is a first-time homebuyer or a repeat buyer. Hence, I calculate the fraction of first-time homebuyer using alternate denominators: all GSE mortgages, or all GSE mortgages with non-missing information on the first-time homebuyers. The geographic aggregation for this regression is zip3-state level (unlike previous regressions which were at census tract level), I use the following equation:

$$y_{zcjt} = \beta_0 + \beta_1 Treament_{zc} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{ct} \qquad (2)$$

Here z indexes areas delineated by 3-digit zip-code and state. Other terms are same as in Equation (1). Table 6 shows the result of regressing fraction of first-time borrowers using Equation (2). We see that the percentage of first-time homebuyer increases by 1 percentage point in the treatment zip3-state area relative to the control zip3-state area. One may have a concern that the data used in this regression is a selected sample of the mortgages that were purchased by the GSE's only. For this to be a valid concern, GSE's incentives, or mandate, of purchasing first-time homebuyer mortgages relative to overall purchase, has to change in the treatment area, but not in the control areas in the year 2005. This seems unlikely to be the case.

Heterogeneous Effect of Free Credit Report

Effect of Free Credit Report: Role of Creditworthiness

I argue that credit report aids in self-assessment of creditworthiness, and mitigates the Type A and B mismatch in the mortgage market. Ceteris paribus, areas where a higher fraction of population is prime are more likely to see its consumers discovering that they are more creditworthy than they thought than the areas where a higher fraction of population is subprime. In other words, areas where consumers have low creditworthiness are less likely to see an increase in the mortgage approval ratio than the areas where consumers have high creditworthiness, after easier access to free credit report is available.

To examine this, I begin with the Federal Reserve Bank of New York and Equifax (n.d.) data on the percentage of subprime population (with credit score <660) in a county. I classify all counties as high (low) creditworthiness if its fraction of prime population is higher (lower) than the *regional mean* (see footnote 28). For this classification, I use the data from the year 1999. This is because the creditworthiness of the population in a county might endogenously change with the onset of the housing boom. Mian and Sufi (2009) suggests that such classifications should be done at a time prior to the start of housing boom.[31]

Table 7 shows the result of regression in Equation (1) for the number of applications per 1000 adult and the mortgage approval ratio, estimated separately for the prime and subprime counties. The estimates suggest that the number of applications and the mortgage approval ratio significantly increased in the treated prime counties relative

31. Mian and Sufi (2009) uses year 1996 to classify the zip codes into prime and subprime. I use the year 1999, as this is the earliest year for which the data is publicly available.

to the control prime counties, but not in the treated subprime counties relative to the control subprime counties. These results provide two insights. First, free credit report seems to result in an increase in the number of applications in prime areas. Second, excessive supply of credit by the lenders in the subprime area is not driving these results because we do not see a statistically significant increase in the subprime areas.

Nonetheless, the county level measure of creditworthiness in the above test is noisy. Hence, I redo the above test using a more precise proxy for the creditworthiness of a locality – the number of establishments by payday lenders. The idea is that payday lenders tend to locate in subprime areas (Prager, 2009). Also, the location of payday establishments is available at a 5-digit zip code level from Survey of County Business Patterns, allowing a cleaner identification of creditworthiness. However, many states restrict payday lending activities Bhutta (2014); Prager (2009). Among the seven pre-FACTA states, only Colorado and the bordering states allow unrestricted payday lending activity. Thus, I conduct this test only for all the census tracts in the counties at the border between Colorado (CO, the control state) and WY, UT, AZ, NM, OK, KS and NE (the treatment states). I classify these census tracts into two sub-samples using average number of payday lenders in census tracts in bordering counties of these states in the pre-treatment year 2004.

Table 8 shows the result of estimating the regression in Equation (1) separately for low and high number of payday lenders (high and low creditworthiness) census tracts. The estimates suggest that even though the applications increased in both high and low creditworthy census tracts relative to the control tracts, the mortgage approval ratio significantly increases only in the high creditworthy areas. These results corroborate the earlier finding that the mortgage approval ratio increases in the prime counties, identified using the county level measure, suggesting that the increased mortgage approval ratio is being enjoyed by the consumers from the prime location.

Effect of Free Credit Report: Role of Education

Now, I investigate the role of consumers' education on the heterogeneous effect of free credit report. Debt products are complex, and thus, the information in the credit report may be complex as well. Thus, we should expect the effect of free credit report on the mortgage approval ratio to be stronger for the more educated consumers than that for the less educated counterparts.

To test this hypothesis, I start with calculating the fraction of adult population, of age between 18 and 64 years, having a graduate or equivalent education in each census tract using data from census 2000. A person is classified as *Graduate* if he or she has an Associate degree, a Bachelor's Degree, or a Graduate *or* Professional degree. I calculate the *regional mean* of the fraction of graduates in a census tract in each region (see footnote 28). A census tract then is classified as high education if its fraction of graduate population is higher than the *regional mean*.

Table 9 shows the result of regressing the number of applications per 1000 adult and the mortgage approval ratio in high and low education areas, estimated separately using Equation (1). We see that number of applications as well as the mortgage approval ratio increased significantly in the high education treatment areas relative to the high education control areas, but it did not increase significantly in the low education treatment areas relative to the low education control areas. This finding is consistent with the enabling role of education in accessing credit – better educated population could assess the information in the credit report better and enjoyed higher mortgage approval ratio than the less educated population, leading to an improved applicant pool.

Effect of Free Credit Report: Role of Income

The costlier a mortgage rejection is for a consumer, the higher should be the effect of free credit report. Here, I investigate the effect of free credit report across income groups. For this I divide the mortgage applications each year into four income groups (income quartiles) and calculate the number of applications per 1000 adult and the mortgage approval ratio.

Table 10 shows the result of regressing the number of applications per 1000 adult and the mortgage approval ratio for each income quartile separately using Equation (1). We see that the increase in applications effect is concentrated among the upper three income quartiles, but the increase in the mortgage approval ratio is significant among the consumers in the lowest income quartile. This is consistent with the idea that the cost of rejection is higher for the low income consumers. Even though the effect of free credit report on the approval ratio for the higher income quartile consumers is ambiguous, overall, we can reasonably infer that the borrower pool improves in the lower quartile.

Mortgage Performance after the Free Credit Report

So far, we have seen that free credit report resulted in the increased mortgage demand and higher mortgage approval ratio in the treated areas relative to the control areas, and this effect was stronger in the prime areas. This suggests that these mortgages were extended to ex-ante creditworthy population. But how did these mortgages perform ex-post? It is plausible that free credit reports lead to an increase in the fraction of *just-marginal* borrowers in the market, which in turn may result in higher mortgage defaults in the treated areas. Another possibility is that the consumers in the treated areas become more aware of their credit situation after the advent of free credit report. If this is true, then the mortgages from the treated areas should become less likely to default after the experiment. Which of these two predictions hold in the data?

I examine the ex-post performance of these mortgages in the GSE data. I examine the default rate, defined as the fraction of total mortgages which misses the scheduled payment by 30-59 days for the first time in a given month after origination. I compare the mortgages originated in the post-event year 2005 ($\text{Def}_{2005,age}$) and the pre-event year 2004 ($\text{Def}_{2004,age}$) in the treated area. I control for the time trend in the mortgage default rate using the mortgages originated in the control areas in same time-period. I define *Adjusted Default Rate* as follows:

$$Adjusted\ Default\ Rate_{age} = (Def_{2005,age} - Def_{2004,age})_{treated} - (Def_{2005,age} - Def_{2004,age})_{control} \quad (3)$$

Here, mortgage age is measured in months since origination. The performance of the mortgage is tracked over six years after its origination.

Figure 8 shows the plot of Adjusted Default Rate with age. A negative adjusted default rate means that the mortgages from the treated areas are less likely to default than those from the control areas. The plot reveals that for most of the months within six years after origination, mortgages in the treated area are less likely to default than the loan in control area. Mean Adjusted Default Rate is -0.012% over six years statistically significant at 1% level (p-value = 0.0000). This means that on average the mortgage in the treated area is 0.012% less likely to default in any given month over six years after origination, relative to a loan from the control area.

Another important observation from this plot is the good performance of these mortgages after the financial crisis of 2007. The mortgage age greater than 48 months in the plot corresponds to the bust years post the financial crisis (48 months is year 2009, measured from 2005). We see that even during the bust years, the mortgages from the treated areas were less likely to default than those from the control areas. Overall, we observe that free credit report induced more mortgage demand and resulted in lower default rates. Increased mortgage demand, together with higher mortgage approval ratio and lower ex-post default rate, suggests better matching in the credit market.

6 Alternative Explanations: Role of Lenders

In this section, I investigate the role of lenders in driving the mortgage origination and approvals higher in the treated areas. We have seen that the heterogeneous effect of free credit report varies by the characteristics of the consumers – creditworthiness, education and income. This suggests that the effect of free credit report is coming through the changes in behavior of consumers. But this does not rule out completely that the lenders are not responding to the effect. In order to isolate the role of lenders, in this section I examine the heterogeneity in the treatment effect based on the characteristics of lenders. If the effects are lender driven, then we should observe the effects to be varying in sync with the characteristics of the lenders. If the effects are not driven by lenders, the effects estimated in different sub-samples created on the basis of characteristics of lenders would be statistically the same. In addition, I also examine the explanation that the lenders increased the supply of mortgage credit to the treated areas due to increase in their incentive to privately securitize the mortgages. Overall, I examine three mortgage supply based explanations and one general credit supply explanation. We would see that none of these explanations are supported in the data.

First, I focus on the density of lenders. If the increase in mortgage origination is driven by lenders, then we would expect that more mortgages are originated, and mortgages are are more likely to be approved in areas where density of lenders is high than those in the areas where density of lenders is low. I calculate the density of lenders as number of HMDA lenders per adult in each census tract in pre-event year 2004. Subsequently, I classify a census tract to have high density of lenders if its density of lenders is more than the *regional mean*.

I regress the volume of mortgages originated and the mortgage approval ratio using the regression in Equation (1) separately for the areas with high and low density of lenders. Table 11 shows the result. Column 1 through 4 shows the result for total amount of mortgage originated (in 1000 USD) per adult in a census tract. We see that the coefficient of $Treat \times Post$ is smaller in specification (2) than in specification (1), and smaller in (4) than in (3). These estimates suggest that the increase in mortgage origination in high lenders' density area in the treated group is smaller than the increase in low lenders' density area in the treated group, controlling for the concurrent changes in the control group. At the bottom of the table, I report the t-test for the difference in coefficient of the interaction term $Treat \times Post$ in high and low lenders' density areas ($High - Low$). The result confirms that the increase in mortgage origination in high lenders' density areas is not statistically different from that in low lenders' density areas. In column 4 through 8, I repeat the analysis for the mortgage approval ratio. The results are similar – there is no statistical difference in the increase in the mortgage approval ratio in areas with a high or low lenders' density. These findings are inconsistent with the explanation that mortgage origination and mortgage approval ratio could have increased solely due to lenders increasing the supply of mortgage.

Second, I examine if the mortgage approval ratio increase due to private (non-government) securitization of mortgages. This is plausible as lenders did lax screening for the just prime borrowers (credit score>620) and sold these mortgages to the private securitization entities (Keys et al., 2010). If the argument that reason for increased approval is private securitization, then we should observe a higher fraction of originated mortgages to be sold to non-government/private securitization entities.

To examines the above prediction, I regress the fraction of successful origination (1) not sold by the lender, (2) sold by lender to government sponsored agencies (Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac), and (3) sold by lender to non-government entities, using the specification in Equation 1. Table 12 shows the results. Coefficients in column 1 and 2 show that the fraction of mortgage kept on own book increased. Coefficients in Column 3 and 4 show that the fraction of mortgage sold to GSEs increased as well. Coefficients in Column 5 and 6 show that there is no statistical change in fraction of mortgage sold to non-GSE/private entities. The finding that there is no change in fraction of mortgages sold to private entities rules out the role of securitization in the observed increase in mortgage origination in the treated areas.

Third, I explore the alternative argument motivated from Mian and Sufi (2009) that lenders increased supply to subprime areas, characterized by the fraction of subprime population at the zip code level. It can be argued that the increased mortgage approval ratio is because lenders increased credit supply to the subprime borrowers in the treatment areas, which we would interpret as an improvement in the borrower pool. Results in Table (7) and (8) show that the effect of free credit report is significant in the prime counties (census tracts), and not significant in subprime counties (census tracts).

I examine if the new mortgages in the treated areas were more likely to be extended to the prime consumers than to the subprime consumers using the credit scores of the applicants. Since the HMDA data do not provide applicant's credit score, I use a subset of the originated mortgages available from the GSEs and described in detail earlier. I regress the number of GSE purchased mortgages in the treatment and the control zip3-state areas separately for prime (credit score $\geq$ 620) and subprime consumers. Table 13 shows the result. Coefficient in specification (1) shows that the number of mortgages originated to the prime consumers increases (by 240) in the treatment zip3-state relative to the control zip3-state areas. This shows that free credit report resulted in increased mortgages to the prime borrowers. It should be noted however that the magnitude estimated in this data is not directly comparable with those estimated in the previous tables using the HMDA data, because the observation unit is zip3-state in the current regression, while it is census tract in the earlier regressions using the HMDA data. Moreover, a caution is warranted in interpreting the result in Table 13. Since this sample is a selected sample of GSEs purchased mortgages only, increase or decrease in mortgage number and amount reflects the combined effect of any demand side factor and changing incentive of GSEs to purchase the prime and subprime mortgages. However, it is not highly likely that the incentive of GSEs to purchase the prime mortgage increased in the treated areas more than that in the control areas in 2005.

The tests examining the role and incentives of lenders so far focuses on the increase in supply of credit *only* to the mortgage or housing sector. However, a general increase in credit supply to non-mortgage related sector might also lead to demand stimulation in the housing sector through spillover. Di Maggio and Kermani (2017) shows that an increase in credit supply to an economy leads to an increase in employment in the non-tradable sector. If for some unobservable reason, the treated areas experience an increase in the supply of credit unrelated to mortgage, they may see an increase in employment in the non-tradable sector, which in turn may spillover and increase the demand for mortgage credit. In this case, the observed increase is not due to free credit report, but it is due to increase in credit supply to non-mortgage related industries.

In order to rule out the role of increase in non-mortgage related supply of credit in increasing the mortgage demand, I examine the employment in non-tradable sector using the DID specification. I follow the classification method of Mian and Sufi (2014) for identifying the non-tradable industry sectors based on the 4-digit North American Industry Classification System (NAICS) codes. There are two methods to classify the industries as non-tradable. First method classifies the retail- and restaurant-related industries as non-tradable. Second method defines industries in the bottom quartile of geographic concentration across counties as non-tradable. I use the annual County Business Pattern data for employment and total payroll in each 4-digit NAICS industry and aggregate them for each county over the industries classified as the non-tradable sector. The observation unit for this test is a county, hence I use a modified DID regression specification as follows:

$$y_{cjt} = \beta_0 + \beta_1 Treament_c \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{ct} \qquad (4)$$

where c indexes a county. Other terms are same as in Equation (1).

I regress county aggregate employment per 1000 adult and aggregate payroll per adult in non-tradable industry sector using Equation 4. If there is an overall increase in employment in the non-tradable sector due to an increase in the non-mortgage related supply of credit, the coefficient of "$Treat \times Post$" would be positive and significant. Table 14 shows the results of the regression. We see that under both the classification methods, not only that there is no difference in employment or wages in the treated counties relative to the control counties, but in fact the wages are lower in the treated counties. Thus, employment or wages in the non-tradable sector did not increase in the treated areas, consistent with absence of increase in supply of credit to non-mortgage related industries. This mitigates the concern that a sudden increase in credit supply to the local economy might be driving the increase in mortgage demand in the treated areas.

7 Robustness

The natural experiment utilized in this paper takes place in the year 2005. The years included in the analysis are from 2000 to 2008 to allow for sufficient post-experiment observation. As the subprime mortgage origination has been argued to be the main reason for the financial crisis of 2008, it is a valid concern that the results in this paper might be coming due to the later years 2007 and 2008. To mitigate this concern, I re-estimate all the tests in this paper by excluding the year 2007 and 2008. The results are provided in the Appendix A. The re-estimated results show that the results are qualitatively and quantitatively similar for almost all the specifications, despite having only two post-experiment observations corresponding to the years 2005 and 2006. Hence, we are reasonably confident that the results documented in the paper are not driven by excessive lending prior to the financial crisis.

8 Conclusion

Credit history plays an important role in accessing financing. Does the high economic cost of obtaining own credit history information exclude some consumers from accessing financing? This is an important and relevant question for the US as well as for other countries which may have less developed retail credit markets and the processes required to obtain own credit report might be obscure, or may not exist at all.

In this paper, I evaluate the causal effect of reduced economic cost of credit report on the retail credit market. I use the enactment of the US federal act *Fair and Accurate Transactions Act 2003* (*FACTA*) allowing free credit report for all consumers as a shock to the availability of credit reports. Seven states had laws allowing its residents to obtain free credit report prior to FACTA. I use the Difference in Differences setting in which the border counties of the early adopting states constitute the control group, and the border counties of the surrounding states constitute the treatment group. This empirical setting avoids the usual endogeneity criticisms of the DID settings which rely on state specific enactment of laws.

I show that the reduced cost of credit report results in increased mortgage applications, improved applicant pool, and increased fraction of the first-time homebuyers. The improved pool effect is observed in high creditworthiness and education areas, and among low income quartile population. Overall, the findings highlight that reducing the economic cost of obtaining information on own credit history allows more consumers to access financing from the credit markets.

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Figure 1:
A Sample Credit Report

This figure shows a sample credit report of a US consumer pulled in the month of April 2020. Only the summary information of the report is presented here, while the specific credit history related details are suppressed. The report contains, inter alia, the details of consumer's credit score, as well as an indication of the available debt capacity. The specific organization of the information in the credit report may vary across different credit reporting agencies. TransUnion®, TrueCredit® and TrueCredit® are registered or unregistered Trademarks of TransUnion or TransUnion LLC, or their respective owners.

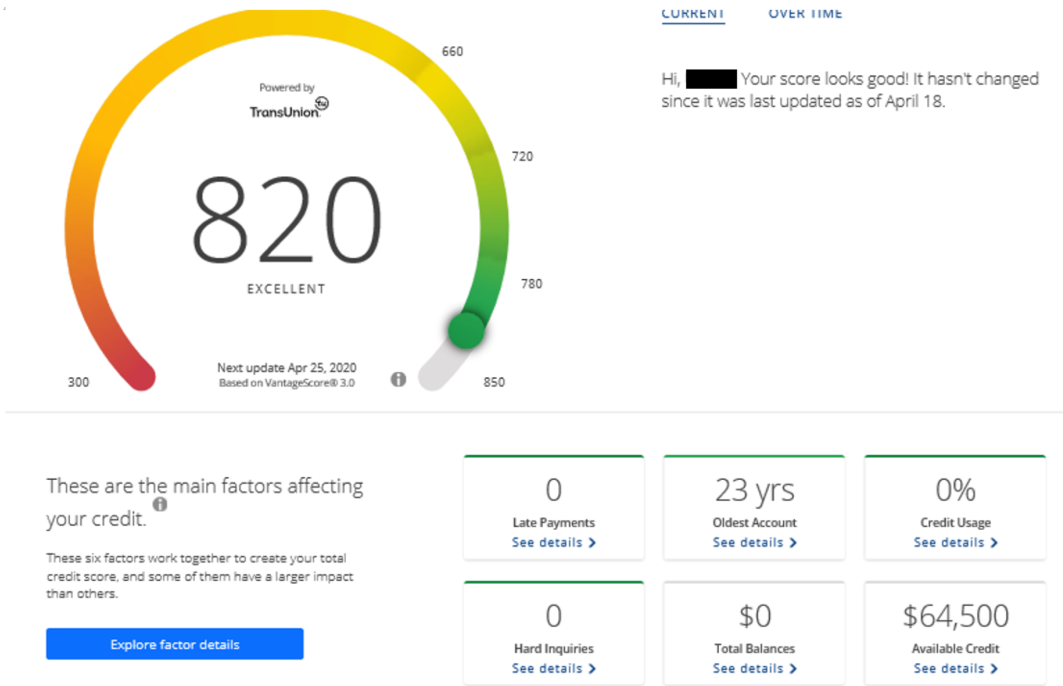


Figure 2:
States providing free credit report prior to FACTA (pre-FACTA states)

This figure shows the seven US states which had enacted free credit report laws – Colorado, Georgia, Maine, Maryland, Massachusetts, New Jersey, and Vermont – in 1997, 1996, 2003, 1992, 1995, 1996, and 1992, respectively. These seven states are referred to as the pre-FACTA states or the control states. In in December 2003, with the enactment of Fair and Accurate Credit Transactions Act (FACTA), free credit report became mandatory in all US states. The website www.annualcreditreport.com was subsequently established in Dec 2004 to distribute the free credit reports (see footnote 11).

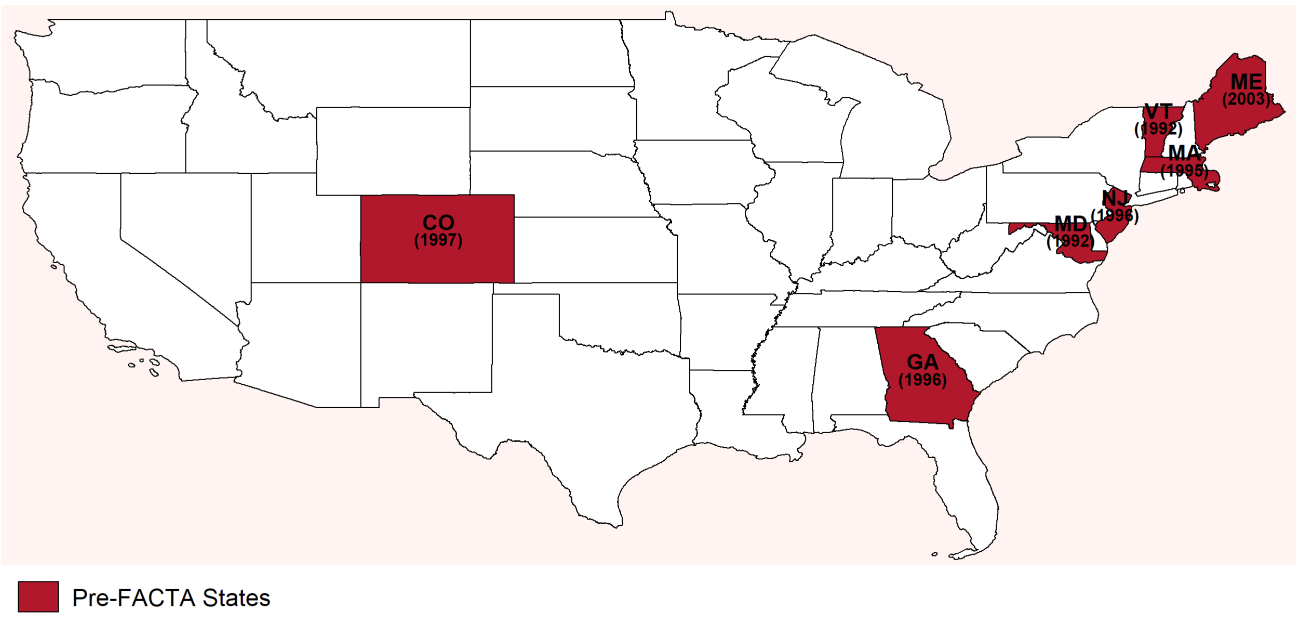


Figure 3:
Empirical Setting: Control and the Treatment States

This figure shows the seven pre-FACTA states serving as the control states and the 26 states that surround the control states, latter serving as the treatment states.

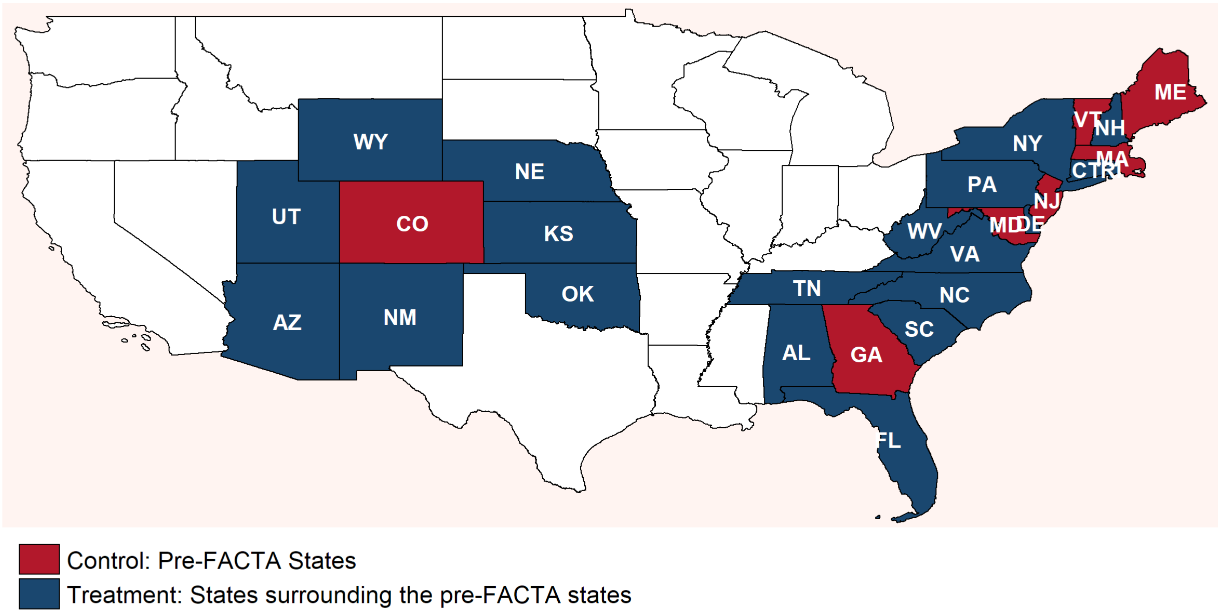


Figure 4:
Empirical Setting: Control and the Treatment Counties

This figure shows the the treatment and the control counties. All the counties that lie at the border of the seven pre-FACTA states constitute the control states. All the counties from the states surrounding the control state and lying at the border between the surrounding state and the control state form the treatment county.

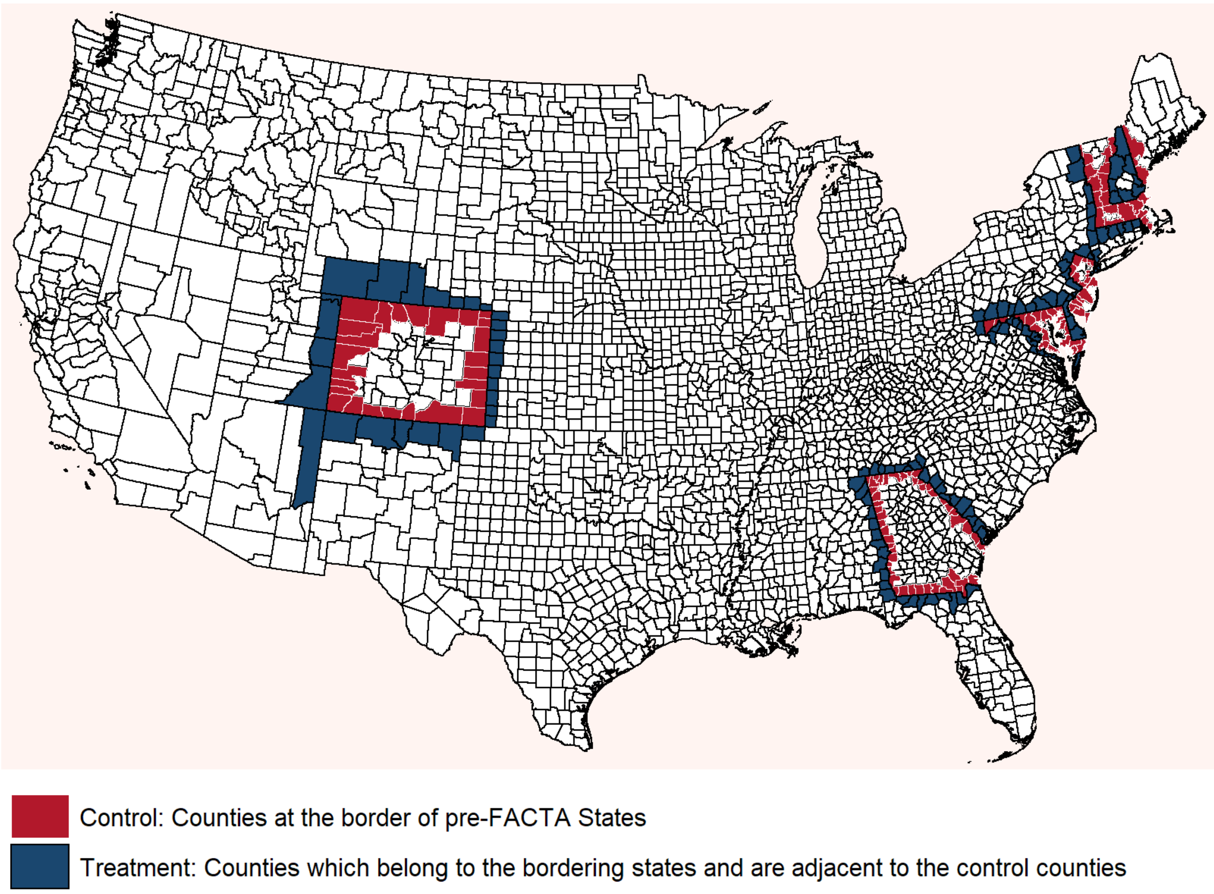


Figure 5:
Difference in Approval Ratio by Years to Treatment

This figure shows the coefficient estimates from regressing "*Approval Ratio*" using the specification:

$$y_{icjt} = \beta_0 + \sum_{k=T-3}^{T-1} \beta_k\, Treament_{ic} \times event_k + \sum_{k=T+1}^{T+4} \beta_k\, Treament_{ic} \times event_k + \alpha_i + \gamma_{j,t} + \varepsilon_{it}$$

where $event_k = 1$ if $t = k$. $event_k = 0$ if $t \neq k$. $T = event\ year$ 2005.

Coefficients are estimated with respect to the base year 2004 ($k = 0$). X-axis represents time relative to the event year 2005, i.e. T = +1 is first post event year period, and so on. Y-axis represents the coefficient estimates β_k's and the 95% confidence interval. The regression includes "*Border* $\times$ *Year*" fixed effects and "*Census Tract*" fixed effects but no economic controls. Other terms in the equation are same as those in Equation 1, and are described in detail in Section 3. Standard error is clustered at the county level.

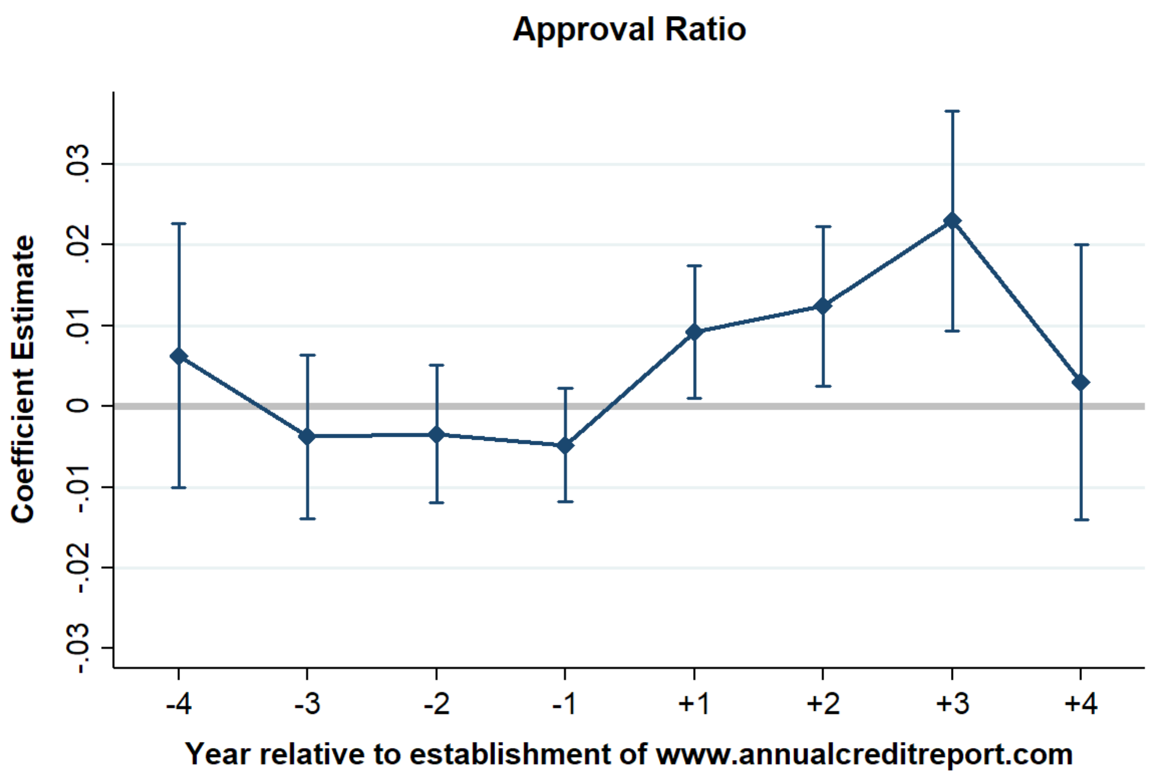
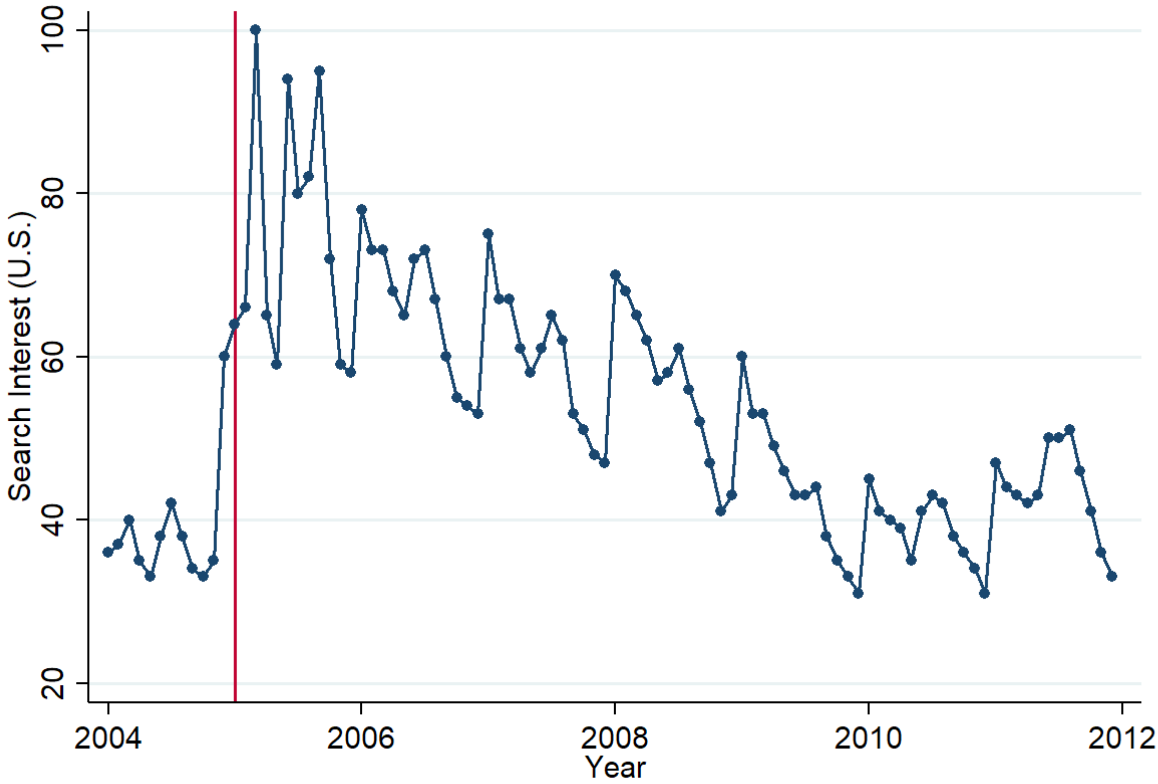


Figure 6:
Google Search Interest for the Term "Free credit report" in the U.S.

This figure shows the plot of Search Interest for the term *Free Credit Report* in the US over time from Jan 1, 2004 till Dec 31, 2011. Numbers on the vertical axis represent search interest relative to the highest point on the chart in the US during the time period of the plot. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term.



Source: Google Trends

Figure 7:
Popularity of the keyword *Free credit report*

This figure shows the difference in mean popularity rank of treatment and control states for the keyword *Free Credit Report* from 2004 to 2008. Popularity score of each state is ranges from 0 to 100, calculated each year. Value of 100 represents the location with the most popularity of the search term as a fraction of total searches in that location. A value of 50 indicates a location which is half as popular. Here, I plot the difference in mean annual popularity of treatment and control states.

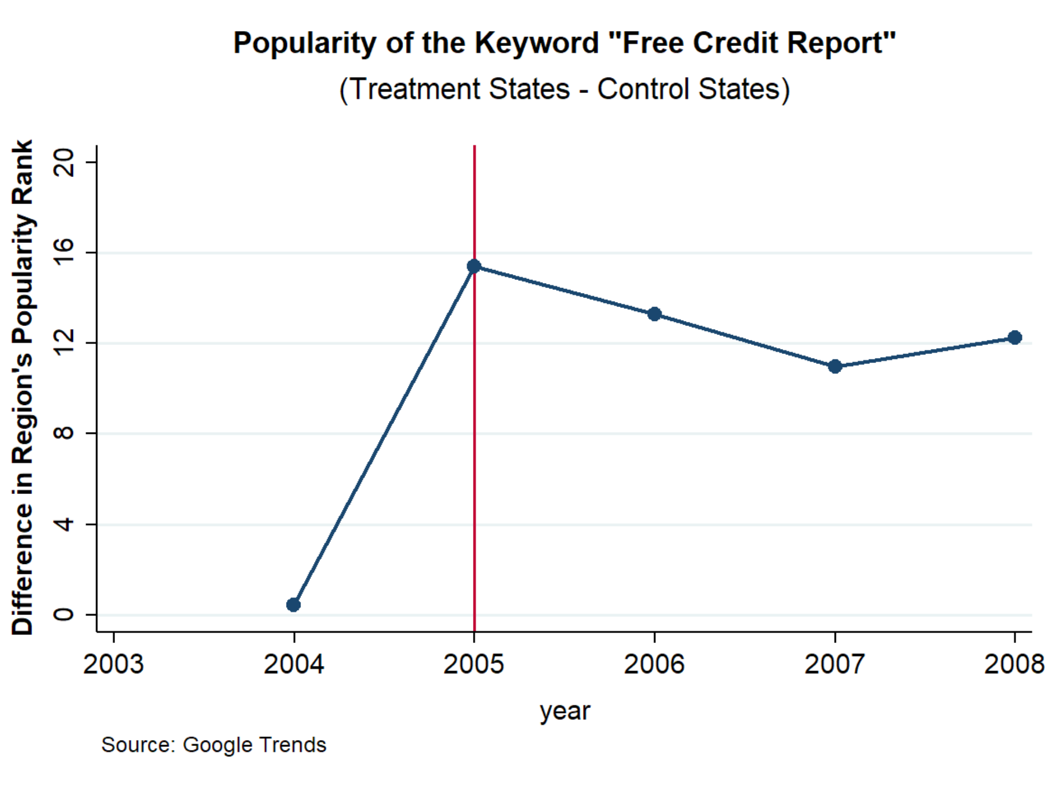


Figure 8:
Free Credit Report and Mortgage Default

This figure shows the Adjusted Default Rate for the sample of 30 year fixed rate mortgages purchased by Fannie Mae and Freddie Mac. I calculate the percentage of total mortgage originated in the pre-event year 2004 and the post-event year 2005 which defaults every month after origination, $\text{Def}_{2005,age}$ and $\text{Def}_{2004,age}$, separately for the treated zip3-state areas and control zip3-state areas. A mortgage is in default when the scheduled payment is delayed by 30-59 days for the first time. I then calculate the Adjusted Default Rate as:

$$\text{Adjusted Default Rate}_{age} = (\text{Def}_{2005,age} - \text{Def}_{2004,age})_{treated} - (\text{Def}_{2005,age} - \text{Def}_{2004,age})_{control}$$

age represent months since origination.

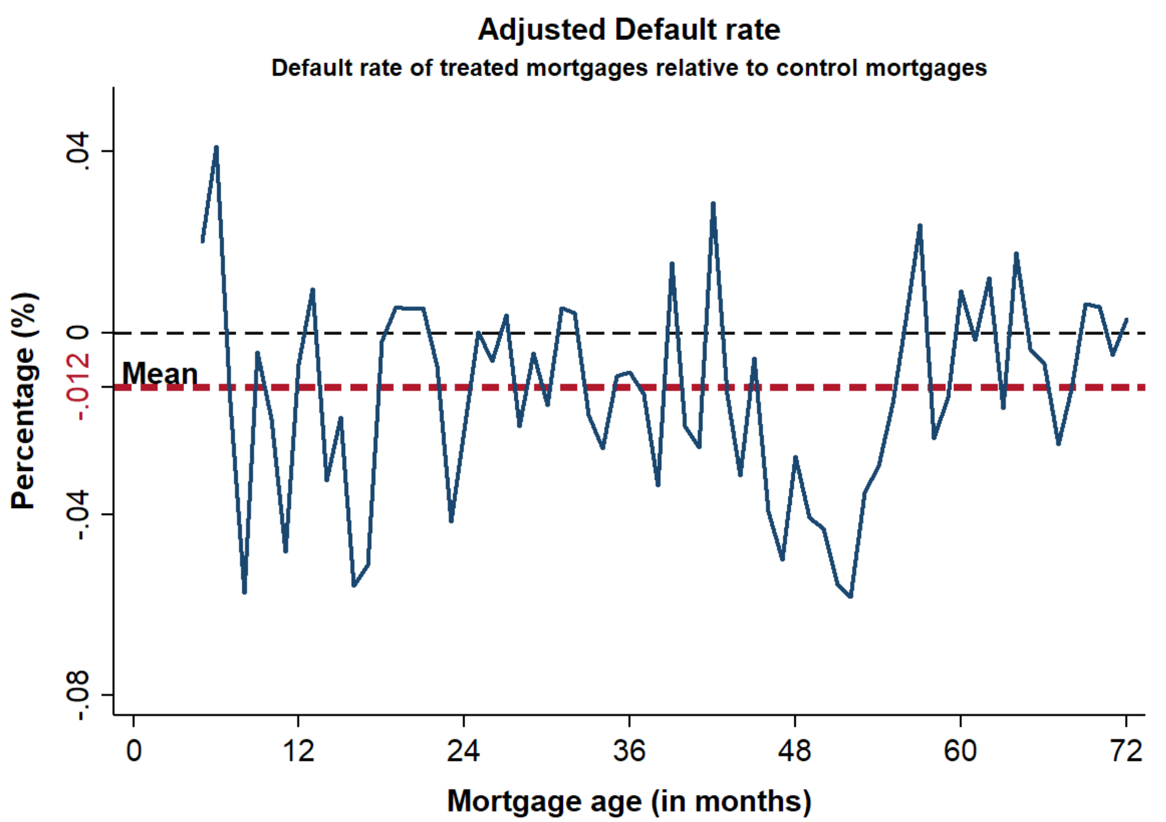


Table 1: Summary Statistics

Panel A shows the statistics for the full sample time period (2000 -2008). Panel B shows the statistics are for the pre-treatment period (2000-2004), and the p-value for the t-test for difference in control and treatment group. *Num of App per 1000 adult* is the number of mortgage applications scaled by the population aged 18 to 64 year in a census tract. *Approval ratio* is the ratio of mortgages originated, or mortgages approved but not accepted to total applications in a census tract. *Deny Credit Hist Ratio* and *Deny Debt-to-inc Ratio* are the ratio of applications denied due to credit history reason and debt to income ratio reason respectively, to the number of total applications in a census tract. *Withdrawal Ratio* is the ratio of applications expressly withdrawn by the applicant to the number of total applications in the census tract. The bottom five variables constitute the *Economic controls*. Δ *Emp.* is the annual growth rate of county employment by all establishments; Δ *Agg Payroll* is the annual growth rate of county aggregate payroll of all establishments; Δ *Total Establishment* is the annual growth rate of county aggregate number of establishments; and Δ *Inc per capita* is the annual growth rate of county income per capita. Δ *State GDP* is the annual growth rate of state gross domestic product.

Panel A: Full Sample (2000 - 2008)

	Full Sample				Control Group (C)				Treatment Group (T)			
	N	Mean	SD	Med.	N	Mean	SD	Med.	N	Mean	SD	Med.
Num of App per 1000 adult	86853	83.40	74.27	66.43	36517	98.38	76.53	77.78	50336	72.53	70.62	56.50
Approval Ratio	82739	0.63	0.13	0.64	35896	0.65	0.12	0.66	46843	0.61	0.13	0.62
Deny Credit Hist Ratio	82739	0.06	0.04	0.05	35896	0.05	0.04	0.04	46843	0.06	0.05	0.05
Deny Debt-to-inc Ratio	82739	0.03	0.03	0.03	35896	0.03	0.02	0.03	46843	0.03	0.03	0.03
Withdrawn Ratio	82739	0.12	0.05	0.12	35896	0.12	0.04	0.11	46843	0.12	0.06	0.12
Δ Emp	90327	0.01	0.05	0.01	37680	0.01	0.04	0.01	52647	0.01	0.06	0.01
Δ Agg Payroll	90328	0.04	0.06	0.04	37680	0.04	0.05	0.04	52648	0.04	0.06	0.04
Δ Total Establishment	90449	0.01	0.02	0.01	37689	0.01	0.02	0.01	52760	0.01	0.02	0.01
Δ Inc per capita	88426	0.04	0.03	0.04	37689	0.04	0.03	0.04	50737	0.04	0.03	0.04
Δ State GDP	90449	0.04	0.02	0.05	37689	0.05	0.02	0.04	52760	0.04	0.02	0.05

Panel B: Pre - Treatment Sample (2000 - 2004)

	Full Sample				Control Group (C)				Treatment Group (T)				(C-T)
	N	Mean	SD	Med.	N	Mean	SD	Med.	N	Mean	SD	Med.	p-val
Num of App per 1000 adult	48391	110.47	82.78	93.53	20306	129.64	84.46	108.77	28085	96.62	78.70	83.20	0.000
Approval Ratio	47043	0.64	0.13	0.65	20084	0.67	0.12	0.68	26959	0.62	0.13	0.63	0.000
Deny Credit Hist Ratio	47043	0.06	0.04	0.05	20084	0.06	0.04	0.05	26959	0.07	0.05	0.06	0.000
Deny Debt-to-inc Ratio	47043	0.03	0.02	0.03	20084	0.03	0.02	0.03	26959	0.03	0.02	0.03	0.000
Withdrawn Ratio	47043	0.12	0.05	0.11	20084	0.12	0.04	0.11	26959	0.13	0.05	0.12	0.000
Δ Emp	51426	0.01	0.06	0.01	21403	0.01	0.04	0.01	30023	0.01	0.07	0.01	0.000
Δ Agg Payroll	51426	0.04	0.06	0.04	21403	0.04	0.06	0.04	30023	0.04	0.07	0.04	0.121
Δ Total Establishment	51536	0.01	0.02	0.01	21409	0.01	0.02	0.01	30127	0.01	0.02	0.01	0.000
Δ Inc per capita	50362	0.04	0.03	0.04	21409	0.04	0.03	0.04	28953	0.04	0.03	0.04	0.000
Δ State GDP	51536	0.05	0.02	0.05	21409	0.05	0.02	0.04	30127	0.04	0.02	0.05	0.000

Table 2: Mortgage Applications and the Mortgage Approval Ratio

This table reports the estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#*Applications* and *Approval Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. The coefficient associated with the *Treat* × *Post* interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include the *Border* × *Year* fixed effects (FE) and the *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
	# Applications	# Applications	Approval Ratio	Approval Ratio
Treat × Post	13.21***	15.19***	0.01***	0.01***
	(2.92)	(3.60)	(2.74)	(2.99)
Census Tract FE	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.814	0.816	0.740	0.735
R^2 (within)	0.011	0.025	0.003	0.006
Observations	86812	84792	82663	80661

Table 3: Owner Occupied Mortgages

Panel A of this table reports the estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio only for the sub-sample of owner-occupied mortgage applications. Panel B reports the result of regressing the fraction of total (successful) applications which are not owner occupied. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#Applications and *Approval Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. *Non-ocp.* represents the fraction of total (successful) applications which are not owner occupied in Column 1 and 2 (3 and 4). The coefficient associated with the *Treat* × *Post* interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include *Border* × *Year* fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Panel A: Applications and Approval Ratio for Owner Occupied Mortgages

	(1)	(2)	(3)	(4)
	# Applications	# Applications	Approval Ratio	Approval Ratio
Treat × Post	10.14***	11.64***	0.01***	0.01***
	(2.74)	(3.30)	(2.88)	(3.05)
Census Tract FE	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.714	0.719	0.624	0.619
R^2 (within)	0.005	0.015	0.001	0.003
Observations	86842	84802	84754	82802

Panel B: Fraction of Owner Occupied Mortgages

	Fraction of total app.		Fraction of successful app.	
	(1)	(2)	(3)	(4)
	Non-ocp.	Non-ocp.	Non-ocp.	Non-ocp.
Treat × Post	0.01	0.01	0.01	0.01*
	(1.54)	(1.53)	(1.62)	(1.68)
Census Tract FE	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.138	0.136	0.115	0.113
R^2 (within)	0.000	0.000	0.000	0.000
Observations	82692	80672	82651	80631

Table 4: Credit History Improvement

This table reports the estimates of the treatment effect on the fraction of mortgage applications denied because of credit history reason and debt to income ratio reason, estimated separately. The regression specification is:

$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}$. See Eq. (1). $\%C.Hist$ ($\%DTI$) is calculated as the ratio of the number of denied applications due to credit history reason (debt to income ratio reason) to the total number of mortgage applications in a census tract. *High Denial Areas* are the census tracts where denial per capita in the pre-event year 2004 was more than the regional mean of denials across the census tracts. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the fraction of mortgage applications denied due to given reason in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	All Areas		High Denial Areas		All Areas		High Denial Areas	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	% C.Hist	% C.Hist	% C.Hist	% C.Hist	% DTI	% DTI	% DTI	% DTI
Treat × Post	-0.003	-0.003	-0.003**	-0.003*	-0.002	-0.001	-0.002	-0.002
	(-1.50)	(-1.52)	(-2.07)	(-1.91)	(-1.08)	(-0.97)	(-1.48)	(-1.20)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.542	0.539	0.575	0.575	0.267	0.266	0.319	0.322
R^2 (within)	0.001	0.001	0.001	0.003	0.000	0.002	0.001	0.006
Observations	82663	80661	39080	38702	82663	80661	39080	38702

Table 5: Credit Shopping

This table reports the estimates of the treatment effect on the fraction of mortgage applications withdrawn. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

% Application Withdrawn is the ratio of applications expressly withdrawn by the consumers to the number of applications in a census tract. The coefficient associated with the *Treat* × *Post* interaction term captures the change in fraction of applications expressly withdrawn by applicants in the treated census tracts relative to the control census tracts. All regressions include *Border* × *Year* fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)
	% Application Withdrawn	% Application Withdrawn
Treat × Post	-0.009***	-0.011***
	(-2.81)	(-3.50)
Census Tract FE	Yes	Yes
Economic controls	No	Yes
Border × Year FE	Yes	Yes
Cluster (County)	Yes	Yes
R^2 (Adj.)	0.340	0.341
R^2 (within)	0.003	0.005
Observations	82692	80672

Table 6: First-time Homebuyers

This table reports the estimates of the treatment effect on the fraction of first-time homebuyers. The regression specification is:

$$y_{zcjt} = \beta_0 + \beta_1 Treament_{zc} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (2).}$$

The mortgage data used in this table is from Fannie Mae and Freddie Mac combined single family loan dataset (GSE data). Dependent variable in Column 1 (2) is the ratio of the number of first-time homebuyer and the total number of mortgages (total number of mortgages for which the information on the first-time homebuyer is not missing) in a given zip3-state area. The coefficient associated with the *Treat* × *Post* interaction term captures the change in proportion of *First Time homebuyer* in the treated 3-digit zipcode-state areas relative to the control 3 digit zipcode areas. All regressions include *Border* × *Quarter* fixed effects (FE) and *Zip3-State* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Denominator - All Applications		Denominator - Applications with Known Status	
	(1)	(2)	(3)	(4)
	% First-time	% First-time	% First-time	% First-time
Treat × Post	0.01***	0.01***	0.01***	0.01**
	(3.25)	(2.80)	(2.69)	(2.21)
Zip3-State FE	Yes	Yes	Yes	Yes
Economic Controls	No	Yes	No	Yes
Border × Qtr FE	Yes	Yes	Yes	Yes
Cluster Zip3-State	Yes	Yes	Yes	Yes
R^2 (within)	0.007	0.014	0.005	0.011
Observations	7468	7468	7473	7473

Table 7: Effect of Free Credit Report: Role of Creditworthiness (County Measure)

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio separately for prime and subprime county. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Prime Counties				Subprime Counties			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	14.33**	16.29***	0.02***	0.02***	4.88	7.24	0.01	0.01*
	(2.36)	(2.64)	(3.11)	(3.39)	(0.97)	(1.63)	(1.55)	(1.95)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.812	0.813	0.786	0.783	0.844	0.847	0.695	0.694
R^2 (within)	0.010	0.020	0.005	0.010	0.002	0.014	0.001	0.003
Observations	37892	36355	37885	36349	41794	41363	41791	41360

Table 8: Effect of Free Credit Report: Role of Creditworthiness (Census Tract Measure)

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio separately for census tracts with low and high number of payday lenders. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}.$$ See Eq. (1).

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. The mean of number of payday lenders in census tracts in counties at the border of Colorado (CO) and surrounding states in 2004 is used to create the two sub-samples. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	# Payday Lenders - Low				# Payday Lenders - High			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	66.20***	69.29***	0.05***	0.05***	43.95***	40.30***	0.01	0.01
	(4.72)	(5.04)	(3.71)	(3.13)	(3.69)	(4.15)	(0.57)	(0.63)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.828	0.832	0.748	0.748	0.811	0.816	0.772	0.773
R^2 (within)	0.128	0.148	0.036	0.041	0.101	0.131	0.003	0.014
Observations	1391	1391	1391	1391	830	830	829	829

Table 9: Effect of Free Credit Report: Role of Education

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio separately for the census tracts with high fraction of graduate population and low fraction of graduate population,. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. Graduate education is defined as *Associate degree*, *Bachelor's Degree*, or *Graduate or Professional Degree*. The fraction of population is calculated as the number of adult aged 18 to 64 having the graduate degree to total number of adult aged 18 to 64 in given census tract, as recorded in Census 2000. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Low Education Area				High Education Area			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	4.85	5.55*	0.01	0.01*	11.24**	13.62***	0.01***	0.01***
	(1.61)	(1.86)	(1.61)	(1.73)	(2.46)	(3.32)	(2.92)	(3.12)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.837	0.840	0.585	0.578	0.836	0.836	0.744	0.741
R^2 (within)	0.003	0.008	0.001	0.004	0.008	0.020	0.003	0.006
Observations	33263	32749	33242	32729	49035	47580	49018	47563

Table 10: Effect of Free Credit Report: Role of Income

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio for each income quartile. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. Income quartiles are calculated every year for a given census tract. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Panel A: Income Quartile 1 and 2

	Income Quartile 1				Income quartile 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	-0.75	-0.98	0.01***	0.02***	1.91**	2.07**	0.01	0.01
	(-0.50)	(-0.67)	(2.99)	(3.96)	(2.02)	(2.17)	(1.02)	(1.40)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.787	0.789	0.257	0.259	0.810	0.812	0.341	0.339
R^2 (within)	0.001	0.004	0.000	0.001	0.004	0.010	0.000	0.001
Observations	83182	81175	79932	77994	83182	81175	81125	79146

Panel B: Income Quartile 3 and 4

	Income Quartile 3				Income quartile 4			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	2.78**	3.29***	0.01	0.01	5.72**	7.12***	0.01*	0.01**
	(2.38)	(3.09)	(1.12)	(1.24)	(2.00)	(2.83)	(1.86)	(2.09)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.799	0.802	0.398	0.394	0.742	0.743	0.379	0.373
R^2 (within)	0.006	0.015	0.000	0.001	0.007	0.018	0.001	0.001
Observations	83182	81175	81645	79649	83182	81175	81349	79350

Table 11: Disentangling the Supply Effect - Heterogeneity in Lender's Density

This table reports the estimates of the treatment effect on the origination volume (in 1000 USD) per adult and the mortgage approval ratio, estimated separately for census tracts having the high and low density of mortgage lenders per capita in 2004. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

Low (*High*) identifies a census tract having the lower (higher) number of HMDA lenders than the *regional mean* number of HMDA lenders (per census tract) within the bordering counties between the given control state and all the treatment states surrounding it in 2004 (See Footnote 28). *Difference* [*High* - *Low*] shows the result for the t-test for difference in coefficient of $Treat \times Post$ in specification *High* and *Low*. Dependent variable in Column 1 through 4 is volume of mortgage originated (in 1000 USD) per adult in a census tract. Dependent variable in Column 4 through 8 is the mortgage approval ratio of mortgage applications at census tracts level. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Volume (in 1000 USD) per Adult				Approval Ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	High	Low	High	Low	High	Low	High
Treat × Post	2.165**	1.227	2.583***	1.792*	0.015***	0.009*	0.015***	0.010**
	(2.16)	(1.11)	(2.79)	(1.83)	(2.99)	(1.89)	(3.22)	(2.05)
Difference [High - Low]		-0.938		-0.791		-0.006		-0.006
p-value		(0.581)		(0.610)		(0.492)		(0.472)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	No	No	Yes	Yes	No	No	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.665	0.596	0.657	0.590	0.750	0.716	0.746	0.712
R^2 (within)	0.006	0.001	0.015	0.005	0.003	0.001	0.007	0.004
Observations	60719	25806	59221	25288	57639	24932	56152	24421

Table 12: Did approval ratio increase due to private securitization?

This table reports the estimates of the treatment effect on the mortgage approval ratio estimated separately for mortgages not sold, sold to government agencies (GSEs), and mortgages sold to other (Non-GSE). The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

Dependent variable is the fraction of total mortgage application that is approved but not sold, in Column (1) and (2); approved and securitized through sale to GSE, in Column (3) and (4); and approved and securitized through non-government institutions, in Column (5) and (6), each calculated at the census tracts level. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Not Securitized		GSE Securitized		Non-GSE Securitized	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fraction	Fraction	Fraction	Fraction	Fraction	Fraction
Treat × Post	0.013***	0.013***	0.040**	0.042**	-0.005	-0.006
	(2.88)	(3.05)	(2.27)	(2.29)	(-0.43)	(-0.44)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.624	0.619	0.000	0.000	0.003	0.002
R^2 (within)	0.001	0.003	0.000	0.000	0.000	0.000
Observations	84754	82802	82692	80672	82692	80672

Table 13: Prime Borrowers - Credit Score Based Evidence

This table reports the estimates of the treatment effect on the number of mortgages originated to prime and subprime borrowers by Government Sponsored Enterprises (GSE's) – Fannie Mae and Freddie Mac – using. The regression specification is:

$$y_{zcjt} = \beta_0 + \beta_1 Treament_{zc} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (2).}$$

Dependent variable in Column 1 is *Number of Originations to Prime Borrowers* (credit score>620) in a given zip3-state area. Dependent variable in Column 2 is *Number of Applications to Subprime Borrowers* (credit score≤620) in a given zip3-state area. The coefficient associated with the *Treat* × *Post* interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include *Border* × *Year* fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)
	#Prime App.	#Subprime App.
Treat × Post	0.21***	0.01*
	(3.15)	(1.93)
Border × Qtr FE	Yes	Yes
Zip3-State FE	Yes	Yes
Cluster Zip3-State	Yes	Yes
R^2 (Adj.)	0.753	0.809
R^2 (within)	0.012	0.007
Observations	7581	7581

Table 14: Employment and Wage in Non-Tradable Sector

This table reports the estimates of the treatment effect of free credit report on aggregate employment and aggregate payroll in the non-tradable sector in a county. The regression specification is:

$$y_{cjt} = \beta_0 + \beta_1 Treament_c \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{ct}. \quad \text{See Eq. (4).}$$

Emp. and *Payroll* are the aggregate employment per 1000 adult and the aggregate payroll (in USD 1000) in non-tradable industry sector in a county, respectively. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $County$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Non-Tradable, Method 1				Non-Tradable, Method 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# Emp.	# Emp.	Payroll	Payroll	# Emp.	# Emp.	Payroll	Payroll
Treat × Post	-1.20	-1.25	-24.82	-27.14	-3.83	-3.53	-202.65*	-190.21*
	(-1.05)	(-1.08)	(-0.94)	(-1.01)	(-1.48)	(-1.36)	(-1.81)	(-1.69)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.946	0.946	0.950	0.950	0.947	0.947	0.934	0.935
R^2 (within)	0.001	0.007	0.001	0.007	0.003	0.016	0.007	0.018
Observations	2313	2280	2313	2280	2313	2280	2313	2280

A Appendix

For robustness, I re-estimate all the tables excluding the years 2007 and 2008. The results are provided in this appendix.

Table A.2: Mortgage Applications and the Mortgage Approval Ratio

This table reports the estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#Applications and *Approval Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include the $Border \times Year$ fixed effects (FE) and the $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)	(3)	(4)
	# Applications	# Applications	Approval Ratio	Approval Ratio
Treat × Post	10.09**	9.08***	0.01**	0.01***
	(2.41)	(2.62)	(2.45)	(2.76)
Census Tract FE	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.819	0.823	0.781	0.775
R^2 (within)	0.005	0.030	0.002	0.004
Observations	67632	66028	65088	63497

Table A.3: Owner Occupied Mortgages

Panel A of this table reports the estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio only for the sub-sample of owner-occupied mortgage applications. Panel B reports the result of regressing the fraction of total (successful) applications which are not owner occupied. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#*Applications* and *Approval Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. *Non-ocp.* represents the fraction of total (successful) applications which are not owner occupied in Column 1 and 2 (3 and 4). The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Panel A: Applications and Approval Ratio for Owner Occupied Mortgages

	(1)	(2)	(3)	(4)
	# Applications	# Applications	Approval Ratio	Approval Ratio
Treat × Post	7.19**	6.19*	0.01**	0.01***
	(2.05)	(1.93)	(2.46)	(2.68)
Census Tract FE	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.708	0.715	0.673	0.668
R^2 (within)	0.002	0.016	0.001	0.002
Observations	67632	66028	65615	64099

Panel B: Fraction of Owner Occupied Mortgages

	Fraction of total app.		Fraction of successful app.	
	(1)	(2)	(3)	(4)
	Non-ocp.	Non-ocp.	Non-ocp.	Non-ocp.
Treat × Post	0.01	0.01*	0.01	0.01*
	(1.64)	(1.88)	(1.64)	(1.88)
Census Tract FE	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.103	0.102	0.086	0.085
R^2 (within)	0.000	0.000	0.000	0.000
Observations	65088	63497	65061	63470

Table A.4: Credit History Improvement

This table reports the estimates of the treatment effect on the fraction of mortgage applications denied because of credit history reason and debt to income ratio reason, estimated separately. The regression specification is:

$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}$. See Eq. (1). *%C.Hist* (*%DTI*) is calculated as the ratio of the number of denied applications due to credit history reason (debt to income ratio reason) to the total number of mortgage applications in a census tract. *High Denial Areas* are the census tracts where denial per capita in the pre-event year 2004 was more than the regional mean of denials across the census tracts. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the fraction of mortgage applications denied due to given reason in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	All Areas		High Denial Areas		All Areas		High Denial Areas	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	% C.Hist	% C.Hist	% C.Hist	% C.Hist	% DTI	% DTI	% DTI	% DTI
Treat × Post	-0.003	-0.004*	-0.004*	-0.004**	-0.002**	-0.003***	-0.003***	-0.003***
	(-1.53)	(-1.95)	(-1.88)	(-1.99)	(-2.36)	(-3.35)	(-2.91)	(-3.18)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.596	0.594	0.643	0.643	0.259	0.258	0.322	0.322
R^2 (within)	0.001	0.003	0.002	0.003	0.001	0.002	0.002	0.004
Observations	65088	63497	30479	30176	65088	63497	30479	30176

Table A.5: Credit Shopping

This table reports the estimates of the treatment effect on the fraction of mortgage applications withdrawn. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

% Application Withdrawn is the ratio of applications expressly withdrawn by the consumers to the number of applications in a census tract. The coefficient associated with the $Treat \times Post$ interaction term captures the change in fraction of applications expressly withdrawn by applicants in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)
	% Application Withdrawn	% Application Withdrawn
Treat × Post	-0.007**	-0.008***
	(-2.54)	(-2.94)
Census Tract FE	Yes	Yes
Economic controls	No	Yes
Border × Year FE	Yes	Yes
Cluster (County)	Yes	Yes
R^2 (Adj.)	0.403	0.399
R^2 (within)	0.002	0.002
Observations	65088	63497

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: First-time Homebuyers

This table reports the estimates of the treatment effect on the fraction of first-time homebuyers. The regression specification is:

$$y_{zcjt} = \beta_0 + \beta_1 Treament_{zc} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (2).}$$

The mortgage data used in this table is from Fannie Mae and Freddie Mac combined single family loan dataset (GSE data). Dependent variable in Column 1 (2) is the ratio of the number of first-time homebuyer and the total number of mortgages (total number of mortgages for which the information on the first-time homebuyer is not missing) in a given zip3-state area. The coefficient associated with the $Treat \times Post$ interaction term captures the change in proportion of *First Time homebuyer* in the treated 3-digit zipcode-state areas relative to the control 3 digit zipcode areas. All regressions include $Border \times Quarter$ fixed effects (FE) and $Zip3\text{-}State$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)
	% First-time (of all apps.)	% First-time (of apps. with known info)
Treat × Post	0.01***	0.01***
	(4.12)	(3.58)
Border × Qtr FE	Yes	Yes
Zip3-State FE	Yes	Yes
Cluster Zip3-State	Yes	Yes
R^2 (within)	0.008	0.006
Observations	5810	5813

Table A.7: Effect of Free Credit Report: Role of Creditworthiness (County Measure)

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio separately for prime and subprime county. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Prime Counties				Subprime Counties			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	14.61**	15.16**	0.01***	0.01***	5.26	4.53	0.01**	0.02**
	(2.21)	(2.51)	(3.22)	(3.85)	(1.22)	(1.17)	(2.23)	(2.59)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.804	0.807	0.814	0.810	0.850	0.853	0.729	0.727
R^2 (within)	0.008	0.025	0.003	0.006	0.002	0.023	0.002	0.004
Observations	30567	29318	29866	28626	36816	36474	35133	34795

Table A.8: Effect of Free Credit Report: Role of Creditworthiness (Census Tract Measure)

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio separately for census tracts with low and high number of payday lenders. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. The mean of number of payday lenders in census tracts in counties at the border of Colorado (CO) and surrounding states in 2004 is used to create the two sub-samples. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	# Payday Lenders - Low				# Payday Lenders - High			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	57.84***	62.20***	0.05***	0.05***	40.42***	36.78***	0.03	0.02
	(4.90)	(5.64)	(3.47)	(3.11)	(4.30)	(5.10)	(1.48)	(1.10)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.828	0.832	0.797	0.797	0.808	0.815	0.819	0.822
R^2 (within)	0.080	0.107	0.038	0.041	0.070	0.114	0.016	0.037
Observations	1131	1131	1095	1095	679	679	676	676

Table A.9: Effect of Free Credit Report: Role of Education

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio separately for the census tracts with high fraction of graduate population and low fraction of graduate population,. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. Graduate education is defined as *Associate degree*, *Bachelor's Degree*, or *Graduate or Professional Degree*. The fraction of population is calculated as the number of adult aged 18 to 64 having the graduate degree to total number of adult aged 18 to 64 in given census tract, as recorded in Census 2000. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $Census\ Tract$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Low Education Area				High Education Area			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	3.41	3.24	0.01	0.01	9.52**	8.84**	0.01***	0.01***
	(1.21)	(1.19)	(0.89)	(1.15)	(2.17)	(2.56)	(2.84)	(3.16)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.848	0.852	0.639	0.631	0.834	0.835	0.783	0.779
R^2 (within)	0.001	0.010	0.000	0.002	0.004	0.027	0.003	0.005
Observations	28047	27626	26347	25933	39500	38322	38672	37500

Table A.10: Effect of Free Credit Report: Role of Income

This table reports estimates of the treatment effect of free credit report on the number of mortgage applications and the mortgage approval ratio for each income quartile. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

#App. and *Apv. Ratio* are the number of applications per 1000 adult and the mortgage approval ratio in a census tract, respectively. Income quartiles are calculated every year for a given census tract. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Panel A: Income Quartile 1 and 2

	Income Quartile 1				Income quartile 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	-0.39	-1.17	0.01**	0.02***	1.67*	1.36*	0.00	0.01
	(-0.31)	(-0.99)	(2.51)	(3.35)	(1.96)	(1.75)	(0.50)	(1.12)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.804	0.808	0.295	0.297	0.822	0.826	0.386	0.383
R^2 (within)	0.000	0.018	0.000	0.001	0.002	0.016	0.000	0.001
Observations	68890	67276	63536	61973	68890	67276	64173	62593

Panel B: Income Quartile 3 and 4

	Income Quartile 3				Income quartile 4			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# App.	# App.	Apv. Ratio	Apv. Ratio	# App.	# App.	Apv. Ratio	Apv. Ratio
Treat × Post	2.11*	1.88*	0.01	0.01	5.11*	5.33**	0.01	0.01*
	(1.91)	(1.93)	(0.89)	(1.16)	(1.94)	(2.54)	(1.46)	(1.79)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.816	0.820	0.436	0.430	0.762	0.765	0.415	0.408
R^2 (within)	0.003	0.021	0.000	0.001	0.004	0.026	0.000	0.001
Observations	68890	67276	64414	62825	68890	67276	64236	62645

Table A.11: Disentangling the Supply Effect - Heterogeneity in Lender's Density

This table reports the estimates of the treatment effect on the origination volume (in 1000 USD) per adult and the mortgage approval ratio, estimated separately for census tracts having the high and low density of mortgage lenders per capita in 2004. The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

Low (*High*) identifies a census tract having the lower (higher) number of HMDA lenders than the *regional mean* number of HMDA lenders (per census tract) within the bordering counties between the given control state and all the treatment states surrounding it in 2004 (See Footnote 28). *Difference* [*High* - *Low*] shows the result for the t-test for difference in coefficient of $Treat \times Post$ in specification *High* and *Low*. Dependent variable in Column 1 through 4 is volume of mortgage originated (in 1000 USD) per adult in a census tract. Dependent variable in Column 4 through 8 is the mortgage approval ratio of mortgage applications at census tracts level. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Volume (in 1000 USD) per Adult				Approval Ratio			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Low	High	Low	High	Low	High	Low	High
Treat × Post	1.692*	0.906	1.520*	0.938	0.013**	0.009**	0.014***	0.012**
	(1.76)	(0.81)	(1.85)	(1.02)	(2.49)	(2.07)	(2.67)	(2.60)
Difference [High - Low]		-0.787***		-0.581***		-0.004***		-0.002***
p-value		(0.000)		(0.000)		(0.000)		(0.000)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	No	No	Yes	Yes	No	No	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.675	0.585	0.668	0.580	0.790	0.760	0.785	0.755
R^2 (within)	0.003	0.000	0.021	0.008	0.003	0.001	0.005	0.004
Observations	47293	20090	46114	19678	45393	19606	44222	19199

Table A.12: Did approval ratio increase due to private securitization?

This table reports the estimates of the treatment effect on the mortgage approval ratio estimated separately for mortgages not sold, sold to government agencies (GSEs), and mortgages sold to other (Non-GSE). The regression specification is:

$$y_{icjt} = \beta_0 + \beta_1 Treament_{ic} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (1).}$$

Dependent variable is the fraction of total mortgage application that is approved but not sold, in Column (1) and (2); approved and securitized through sale to GSE, in Column (3) and (4); and approved and securitized through non-government institutions, in Column (5) and (6), each calculated at the census tracts level. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Not Securitized		GSE Securitized		Non-GSE Securitized	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fraction	Fraction	Fraction	Fraction	Fraction	Fraction
Treat × Post	0.012**	0.013***	0.042**	0.040***	-0.005	-0.006
	(2.46)	(2.68)	(2.36)	(2.62)	(-0.43)	(-0.55)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.673	0.668	0.000	-0.000	0.003	0.002
R^2 (within)	0.001	0.002	0.000	0.000	0.000	0.000
Observations	65615	64099	65088	63497	65088	63497

Table A.13: Prime Borrowers - Credit Score Based Evidence

This table reports the estimates of the treatment effect on the number of mortgages originated to prime and subprime borrowers by Government Sponsored Enterprises (GSE's) – Fannie Mae and Freddie Mac – using. The regression specification is:

$$y_{zcjt} = \beta_0 + \beta_1 Treament_{zc} \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{it}. \quad \text{See Eq. (2).}$$

Dependent variable in Column 1 is *Number of Originations to Prime Borrowers* (credit score>620) in a given zip3-state area. Dependent variable in Column 2 is *Number of Applications to Subprime Borrowers* (credit score≤620) in a given zip3-state area. The coefficient associated with the *Treat* × *Post* interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include *Border* × *Year* fixed effects (FE) and *Census Tract* FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	(1)	(2)
	#Prime App.	#Subprime App.
Treat × Post	0.20***	0.00
	(2.93)	(1.08)
Border × Qtr FE	Yes	Yes
Zip3-State FE	Yes	Yes
Cluster Zip3-State	Yes	Yes
R^2 (Adj.)	0.760	0.845
R^2 (within)	0.008	0.002
Observations	5897	5897

Table A.14: Employment and Wage in Non-Tradable Sector

This table reports the estimates of the treatment effect of free credit report on aggregate employment and aggregate payroll in the non-tradable sector in a county. The regression specification is:

$$y_{cjt} = \beta_0 + \beta_1 Treament_c \times Post_T + \delta \times Economic\_controls + \alpha_i + \gamma_{j,t} + \varepsilon_{ct}. \quad \text{See Eq. (4).}$$

Emp. and *Payroll* are the aggregate employment per 1000 adult and the aggregate payroll (in USD 1000) in non-tradable industry sector in a county, respectively. The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated census tracts relative to the control census tracts. All regressions include $Border \times Year$ fixed effects (FE) and $County$ FE. All variables are defined in Table 1. Standard errors are clustered by county. t-statistics is reported below the coefficient in parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Non-Tradable, Method 1				Non-Tradable, Method 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	# Emp.	# Emp.	Payroll	Payroll	# Emp.	# Emp.	Payroll	Payroll
Treat × Post	-1.39	-1.29	-18.49	-20.90	-5.23*	-4.61*	-206.18**	-187.93**
	(-1.13)	(-1.05)	(-0.74)	(-0.85)	(-1.91)	(-1.70)	(-2.13)	(-2.03)
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	No	Yes	No	Yes	No	Yes	No	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.952	0.952	0.961	0.960	0.952	0.953	0.946	0.947
R^2 (within)	0.001	0.009	0.001	0.007	0.006	0.014	0.009	0.016
Observations	1799	1774	1799	1774	1799	1774	1799	1774