Know Thyself: Free Credit Reports and the Retail Mortgage Market*

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Abstract

Under imprecise creditworthiness information, borrowers may make erroneous credit decisions. Credit reports—which record one's creditworthiness—became free in the entire U.S. in 2005, while they already had been free in seven states. Exploiting this in a difference-in-differences setting, this paper shows that cheaper credit reports to consumers improved mortgage market outcomes. The applications, approvals and borrowing in high-creditworthy areas increased, and defaults and subprime population fraction decreased. Also, first-time homeowner proportion increased, and lenders' financial performance improved. Additional findings, including increased interest rates, suggest a demand-driven improvement in applicant pool, as consumers receive precise creditworthiness signal from their reports.

JEL Codes: D12, D83, G21, G28, L51

Keywords: Credit Reports, Information Provision to Consumers, Household Finance, Mortgages, Regulation of Credit Information

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Introduction

Consumers primarily take out mortgages to finance housing. There were about 150 million consumer mortgage applications in the U.S. between 2000 and 2008, and interestingly, one fifth of these were rejected. Underneath these rejections lies an interesting pattern: the most frequent rejection reason was consumers' credit history, not debt-to-income ratio. Specifically, 28% of all rejections, or 39.4% of all rejections that mentioned a denial reason, were due to consumers' credit history (8.34 million such rejections). Debt-to-income ratio, which captures borrowers repayment ability, accounted for just half as many rejections. Given non-trivial rejection costs that include $300–400 in application fees and increase in future rejection probability and interest rate, it is surprising that more consumers were rejected for having bad credit history than for having low repayment ability. Do retail consumers have imperfect information about their creditworthiness? If not, those with bad credit history would not have applied, and would have saved the application and rejection costs. It seems likely that such erroneous credit-related decisions emerge due to imperfect information consumers have about their creditworthiness.

Multiple evidence indeed highlight that consumers' information of their creditworthiness is inadequate. Survey of Consumer Expectations (SCE) Credit Access Survey reveals that about 12% of the U.S. consumers don't know their credit score, and 20% have either never checked their credit reports, or checked it more than two years ago (FRBNY, 2013–2020). Similarly, ~37% of the respondents in a U.S. mail survey study wrongly assessed their credit rating (Perry, 2008). When faced with uncertainty over creditworthiness, one may not even apply for credit anticipating a rejection despite needing credit. Such consumers are commonly referred to as the *discouraged borrowers*. SCE data show that among those consumers unlikely to apply for mortgage or refinance, 13% are discouraged. Similarly, across all credit types, a staggering ~15% of the U.S. households are discouraged (Survey of Consumer Finances, 1998–2007). Under creditworthiness-related uncertainty and poor understanding, many potential borrowers might be discouraged from applying for credit because they overestimate the rejection probability.

The purpose of this paper is to examine the effect of lowering consumers' economic cost of accessing their credit-history information on credit market outcomes. Specifically, this paper evaluates the causal effect of providing consumers free credit reports—an authoritative information source of their creditworthiness—on mortgage demand and approval ratio. This

question is important because on one hand consumers seem to have poor understanding of their creditworthiness, on the other hand they rarely seek to access their credit reports. Out of approximately 1 billion credit reports generated annually in the U.S. in early 2000's, a mere 1.6% were used by consumers (Avery, Calem, & Canner, 2004). It is likely that high economic costs of accessing the reports contributes to its low usage, as accessing it involves, in addition to monetary and search cost, the costs imposed by limited financial literacy and awareness.

Making the credit reports free had three main effects on the mortgage market outcomes. First, mortgage demand and approval ratio increased, and subprime population fraction decreased. Second, good quality borrowers seem to be behind the increased demand: origination was higher in more creditworthy areas and among prime consumers, and new mortgages were less likely to be defaulted upon. Finally, more first-time homebuyers took out mortgages, and lenders experienced improvements in their financial performance.

What mechanism might be at play here? This paper proposes that consumers self-assess their creditworthiness better when economic cost of accessing credit reports is lowered, and that in turn shapes the credit market outcomes (*consumer self-learning*). Lenders rely on credit reports to assess creditworthiness of applicants as these reports convey crucial financial information on consumers e.g., their credit history and borrowing capacity (Figure I). Thus, before making a credit application, by using the information in their credit reports, consumers can acquire accurate knowledge of their creditworthiness.[1] With this, they can sort themselves better in the credit market: good borrowers may stay-in/enter the market, while those with bad credit history may search for a suitable lender, say a subprime lender, or do not apply/exit the market. This sorting leads to changes in the credit demand and approval ratio.

A key challenge in examining the link between consumers' economic costs of credit reports and the credit market outcomes is to establish causality. This paper addresses it using a natural experiment in the U.S.—the enactment of the federal *Fair and Accurate Transaction Act of 2003* (FACTA)—that led to a close-to-exogenous reduction in the cost of credit reports. The FACTA made access to three credit reports free annually from 2005 for all consumers, through the website www.annualcreditreport.com. However, seven states—Colorado, Georgia, Maine, Maryland, Massachusetts, New Jersey, and Vermont—had already been allowing their resi-

[1] Inaccurate self-assessment of creditworthiness, contributed by lack of financial knowledge and complexity of debt products, leads to worse financial outcomes (Courchane, Gailey, & Zorn, 2008). Further, consumers underestimate their student (credit card) debt by as much as 25% (37%) (Brown, Haughwout, Lee, & Van Der Klaauw, 2011). Also, credit reports itself may contain mistakes large enough to affect assessment by lenders (Avery et al., 2004).

dents free credit reports before the FACTA. So, consumers from all states except these seven (the pre-FACTA states) saw a reduction in cost of the reports in 2005. The law also raised general awareness about the reports, thereby reducing the overall economic costs of the reports.

This paper deploys the aforementioned reduction in cost of credit reports in a difference-in-differences (DID) design to establish the causal link. In this design, the control group consists of the seven pre-FACTA states, and the treatment the states bordering the control states. The event (treatment) year is 2005. Further, by restricting the focus to a narrow geographic area encompassing *only* the counties at the border between the treated and control states, the empirical design filters out the effect of local economic conditions on the outcomes of interest.

This empirical design mitigates the endogeneity in the treatment and control assignment. Recall that the treatment is assigned not by states' local laws, but by the federal law, FACTA, that was binding on all the states. So, the treated states did not *choose* to become treated. At the same time, the "control" is assigned to the pre-FACTA states due to their local laws that were already in force at the time of the event. In spite of this reassuring assignment scheme, the enactment of FACTA in 2003 could still be argued to be an endogenous response to the prevailing conditions. The circumstances of the enactment, however, suggest otherwise. As it happened, most of the FACTA provisions were not new, but were consolidated from another existing federal law, the *Fair Credit Reporting Act of 1970* (*FCRA*), to which FACTA added the free credit report provision. Owing to a sunset clause added to the FCRA in 1996, it was bound to expire in 2003. Hence, the upcoming expiration of FCRA in 2003, not the contemporary economic conditions, brought FACTA to fruition (Nott & Welborn, 2003). Note also that since most of the FACTA provisions, other than the free credit report provision, were already in place under the FCRA, the concern that they may create confounding effects is limited.

The empirical investigation focuses on mortgage-related outcomes aggregated at the census tracts level—a sub-county geographic area roughly encompassing a population of about 4,000. Comparing the census tracts in the control and treated counties, the DID estimates suggest that free credit reports resulted in an increase of 13.8%–16.0% in mortgage applications, and an increase of 1–2 percentage points in the approval ratio. In dollar terms, the demand increase was about $38.1 billions, and increase in origination due to higher approval was about $5.5 billions, aggregated *only* across the treated bordering counties (not all counties from all states). Finally, the growth rate of house prices increased, albeit statistically weakly, by ~1.7 percentage points. These estimates incorporate *Census Tract* and "*Border* $\times$ *Year*" fixed effects, and are robust to

the addition of time-varying controls capturing county- and state-level economic conditions.

Since the event took place in 2005, close to the 2008 financial crisis, a natural question arises: whether the increase in demand came from occupancy- or investment-seeking borrowers? Within the owner-occupied mortgages, the estimates for increase in demand and approval ratio are similar to those observed in the whole sample. Then, tests for changes in the composition of demand show a minor increase of 1 percentage point in the non-owner-occupied mortgages as the fraction of total applications (or, successful applications). In essence, surge in demand appears to have mostly come from the occupancy-motivated borrowers.

A spike in mortgage origination could be detrimental to the economy if the defaults too increase subsequently. Over a six-year period since inception, mortgages from the treated areas originated in the event year were less likely to be defaulted upon than those originated in the pre-event year, after accounting for the trends in the control areas. Besides, this superior performance persisted through the 2008 financial crisis. The findings—more origination but fewer defaults—suggest that the borrower pool improved in response to the free credit reports.

The next set of tests examines the *consumer self-learning* channel. To start with, the subprime population fraction in the treated counties with respect to the control began to decline a year after the event, likely due to market entry by new prime borrowers and/or increased subprime-to-prime transition. Any which way, the treated areas saw slight improvements in creditworthiness, plausibly from improved creditworthiness knowledge among consumers.

Three further mortgage-market measures shed light on the channel. *First,* if consumers self-learn their creditworthiness from credit reports, then in aggregate, the likelihood of rejections due to credit history should decrease. Indeed, the credit-history denials decreased in the treated areas by 0.3 percentage points, though significant only in the *ex-ante* high rejection areas, while debt-to-income denials did not decrease. *Second,* the certainty over application acceptance should be higher among borrowers that are better-learned of their creditworthiness, allowing them to apply to fewer lenders *ex-ante* (confident applicant) and saving the costs of multiple applications. Consistent with it, withdrawal of in-process applications dropped by 0.9 percentage points in the treated areas. *Finally,* among the originated mortgages, the fraction of first-time homebuyers increased by 1 percentage point in the treated areas, clearly showing entry by *new* borrowers.

It is important to examine if the results are supply-driven, instead of demand-driven as proposed. Lenders may react to the knowledge that their potential clients could now access free

credit reports under the FACTA. Multiple evidence, however, favor the demand-explanation. To start with, the mortgage applications increased, and consumer interest in free credit reports, measured using Google Search Interest for the keyphrase *"Free Credit Reports"*, heightened in the treated areas after the event. Then, interest rates on the mortgages purchased by Government-sponsored Enterprise (GSE) in the treated areas rose by ~1.1 basis points, controlling for credit score and property attributes, and despite a highly elastic mortgage supply. Had the increased origination been supply-driven, the interest rates would have decreased.

Furthermore, three heterogeneity tests show that the demand and approval ratio responded to different degrees across areas in a manner consistent (inconsistent) with the demand- (supply-) related factors. *Firstly,* there was no difference in areas with high and low lender density, a supply-related factor. *Secondly,* effects were stronger in areas with high consumer creditworthiness, a demand-related factor. *Finally,* the increase in approval ratio was more for the lowest income-quartile applicants. As the marginal propensity to lend to low-income applicants is low, (Agarwal, Chomsisengphet, Mahoney, & Stroebel, 2018), approvals to them may not have increased without lender-perceived improvement in the pool. Overall, tests examining the heterogeneous effects and interest rates underscore that demand-related factors were instrumental in the increased origination.

Other market patterns that emerged around the event further aid our understanding of the effects. *First,* the fraction of mortgages sold to non-GSEs did not increase, ruling out private securitization as an explanation for the increased origination (Keys, Mukherjee, Seru, & Vig, 2010). *Second,* the increase in mortgage to treated prime borrowers was 30 times larger than that to the treated subprime borrowers, making subprime origination an unlikely explanation as well (Mian & Sufi, 2009). *Third,* banks with *ex-ante* higher mortgage activity in the treated areas seem to enjoy improvements in net interest margin and return on equity and assets.

This paper primarily relates to the literature on effects of information provision on credit market participants. This is the first paper to show that consumers' economic costs of credit reports, when lowered, leads to improved mortgage market outcomes in a way consistent with improved borrower pool. In a field experiment, Homonoff, O'Brien, and Sussman (2019) find that borrowers are less likely to default when provided with information on their FICO® scores. Similarly, bank customers who enroll in free FICO scores program are less likely to default, reduce credit utilization, and increase credit card spending (Mikhed, 2015). Moreover, when financial product disclosure is increased, sophisticated borrowers default less, and when fi-

nancial product is standardized, unsophisticated borrowers default less (Kulkarni, Truffa, & Iberti, 2018). Also, consumers increase mortgage borrowing after bankruptcy flags from their credit reports are removed (Dobbie, Goldsmith-Pinkham, Mahoney, & Song, 2016). It also leads to aggregate welfare loss, cheaper credit for poorer defaulters, and expensive for poorer non-defaulters (Liberman, Neilson, Opazo, & Zimmerman, 2018).

This paper also relates to the extensive literature on financial literacy. Low financial literacy leads to detrimental economic outcomes, such as high mortgage delinquency and foreclosure (Gerardi, Goette, & Meier, 2010), poor mortgage choice (Moore, 2003), and large debt (Lusardi & Tufano, 2009; Stango & Zinman, 2009). Further, field experiments reveal that less financially literate distressed borrowers benefit less from loan-modification contracts (Hundtofte, 2017), and educational intervention improves consumers financial product purchases (Balakina, Balasubramaniam, Dimri, & Sane, 2020). This paper shows that providing free credit reports results in increased mortgage demand and lower defaults.

All in all, we learn that imprecise creditworthiness information among consumers likely play a role in frequent mortgage denials due to credit history and in *discouraging* potential borrowers from applying for mortgage. This paper shows that reducing economic costs of credit reports to consumers improves the market outcomes in a manner consistent with improvements in the borrower pool. Though the findings in the paper pertain to the mortgage market, they are equally relevant to any decision by consumers regarding credit when knowledge of their creditworthiness is imperfect. Moreover, as these findings are causal in nature, a policy intervention aimed at educating consumers of their creditworthiness may yield similar results.

The rest of the paper is organized as follows. Section (1) describes the U.S. laws related to consumers' access to credit reports, Section (2) presents the research design, and Section (3) details the data used in this paper. Section (4) presents the results for mortgage market outcomes, and Section (5) contains supplementary results that aid interpretation of the findings. Finally, Section (6) concludes the paper.

1 U.S. Laws Governing Consumers' Access to Credit Reports

The FCRA governed consumer credit information-related laws before FACTA. Even under the FCRA, consumers had the right to see the contents of their credit reports, except for the credit score, under specific and restrictive provisions. For example, a consumer could receive a free

report if he/she made 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 (Avery, Calem, Canner, & Bostic, 2003).[2] The 1992 amendment to the FCRA mandated that the cost of disclosure of credit information should be reasonable, while that in 1996 capped the cost at $8. The latter also provisioned the law to lapse in 2003.

Even though the FCRA allowed free credit reports at the federal level under specific circumstances, consumers rarely proactively requested their credit report for own use. Out of approximately 1 billion credit reports generated annually, only 1.6% were disclosed to consumers (Avery et al., 2004). Of these 1.6%, only 5.25% were proactively requested by consumers, while 94.75% were disclosed to consumers under the FCRA provisions mentioned earlier (Nott & Welborn, 2003).[3] Thus, only 0.084% of all credit reports generated were disclosed to consumers as a result of their own request.

The pre-FACTA states had enacted local laws to allow the residents free credit reports (Panel A of Figure II). For example, through The State of Colorado SENATE BILL 133, the state enacted its free credit report law on April 21, 1997. Section 4, paragraph (E) of this bill added the following to Title 12, Article 14.3-104 of the Colorado Statute:

> *(E): Each consumer reporting agency shall, upon request of a consumer, provide the consumer with one disclosure copy of his or her file per year at no charge whether or not the consumer has made the request in response to the notification required in paragraph (a) of this subsection.*

The 1996 amendment to the FCRA added the sunset clause to it, mandating it to expire in 2003. In order to make its provisions permanent, the FACTA was enacted on December 4, 2003, with a new key provision added: free annual disclosure of credit reports to consumers by each of the three national credit reporting agencies.

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[2] An adverse action notice can be sent to a consumer by the *user* of a 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. 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.

[3] Breakdown of the 94.75% credit reports disclosed under FCRA provisions: 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.

2 Empirical Research Design

As discussed, this paper uses a DID setting in which the seven pre-FACTA states constitute the control group, and the states bordering these states the treatment group. Further, the final sample consists of only the counties lying at the border of the control states and surrounding treatment states. Panel A of Figure (II) depicts the pre-FACTA states and the years they adopted local free credit report laws, and Panel B shows the treatment and control states. Figure (III) shows the counties at the border of these states. The event is year 2005 when www.annualcreditreport.com was established to distribute the free credit reports.[4]

Main regressions use the following two-way fixed-effects estimator equation:

$$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt} \qquad (1)$$

where Y_{icsjt} is the outcome variable for a census tract i from a county c lying at the border between treatment state s and control state j. Recall that there are seven control states, thus j ranges from one to seven. t indexes years 2000–2008 and $Post_t$ takes value 0 for year $t < 2005$ and value 1 for year $t \geq 2005$. $Treatment_{icsj}$ is 0 for all the census tracts i in counties c from control states j, and is 1 for those from treatment states s. α_i represents "*Census Tract*" fixed effects. It accounts for any time-invariant differences across census tracts at a highly granular geographic area encompassing about 4,000 population. Further, clustering the standard errors at the county level accounts for correlation in error terms for the observations from census tracts belonging to the same county.

The key identifying assumption for this DID estimate to be causal is that the treatment states would have had similar trends to the control states in the absence of the treatment (parallel-trends assumption). Though it is unverifiable, Figure (IV) examines the trend of mean approval ratio across the two groups before the event. It seems to be parallel (Panel A).

Furthermore, Panel B of Figure (IV) plots the coefficients (β_k) from regression of *Approval Ratio* according to the following specification:

$$Y_{icsjt} = \beta_0 + \sum_{k=T-3}^{T-1} \beta_k \, \text{Treatment}_{icsj} \times \text{Event}_k + \sum_{k=T+1}^{T+4} \beta_k \, \text{Treatment}_{icsj} \times \text{Event}_k + \alpha_i + \gamma_{j,t} + \varepsilon_{icsjt}$$

[4] The website was rolled-out in four phases from Dec 2004 to Jan 2005. Phase I rollout was on Dec 1, 2004 in 13 states: *AK, AZ, CA, CO, HI, ID, MT, NV, NM, OR, UT, WA, and WY*. Phase II rollout was on Jan 3, 2005 in 12 states: *IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, and WI*. Phase III rollout was on Jan 6, 2005 in 11 states: *AL, AR, FL, GA, KY, LA, MS, OK, SC, TN, and TX*. Phase IV rollout was on Jan 9, 2005 in the remaining 14 states and DC.

where $\text{Event}_k = 1$ if $t = T - k$. $\text{Event}_k = 0$ if $t \neq T - k, k = \{-3, 4\}$. T = Event year 2005. These coefficients represent the difference in approval ratio for the two groups over the years relative to the pre-event year (2004). We see from the plot in Panel B that for the most part no significant difference exists between the treated and control census tracts before the event, but the difference becomes significant afterwards. Overall, the two plots in Figure (IV) together provide reasonable assurance that the parallel trend assumption is satisfied in the current setting.

When analyzing mortgage market outcomes, it is necessary to account for local economic conditions. The regression Equation (1) achieves this through *Economic controls* and "*Border* × *Year*" fixed effects. *Economic controls* include county- and state-level variables that capture local economic conditions—annual growth rate of county income per capita, county's aggregate employment, and state's gross domestic product (GDP). $\gamma_{j,t}$ in Equation (1) represents "*Border* × *Year*" fixed effects, where j refers to the border of a control state. This flexibly accounts for any time-varying regional economic shocks that may affect bordering states across different years. Consider a control state CO. All census tracts from the counties at the border between CO and the surrounding states—WY, UT, AZ, NM, OK, KS, and NE—take the same value (j), thus are grouped as one unit. Thus, the fixed effects only utilize the variation in the outcome variables *within* each such contiguous geographic areas. Finally, the interaction with year accounts for any year specific cross-geography shock.

Another underlying assumption in this setting is that higher cost of credit reports leads to its lower usage. Given that a report costs only around USD 8, one may wonder whether this is large enough to keep consumers from obtaining their credit reports. Note that the economic costs of accessing credit reports may still be high for consumers, especially for financially less knowledgeable ones, as economic costs include the knowledge whether such reports exist, where to obtain these from, and what role do they play in a mortgage process.

The credit reports usage data do support the above assumption. The usage were low in general, and were even lower in the treatment states before FACTA was enacted. *First*, recall that only 0.084% of about 1 billion credit reports issued annually are consumer-requested. Assuming each of these reports to be requested by a separate consumer, 0.84 million consumers accessed their credit reports, while the annual mortgage applications around 2004 numbered about 16.8 millions. So, even if all these reports were requested by mortgage-seeking borrowers, *less than 5%* of the mortgage applicants had checked their credit reports.[5] *Second*, the data

[5] This may be why the Federal Reserve Board actively encourage consumers to check their credit reports—*It can be*

from testimony in the U.S. senate hearing confirms the stark difference in the usage of credit reports in the pre-FACTA states and the rest. Relative to the national average, its usage was 250% higher in GA, 204% higher in MD, 153% higher in CO, 35% higher in NJ, and 25% higher in MA (U.S. Senate. 108th Congress, 2004a).[6]. *Third*, the SCE data suggest that even a decade after credit reports became free, consumers who report they are unaware of their credit score is ~12%, and those who checked their report either never or at least more than two years ago is ~20% (see the Results section).

We further need to ensure that the experiment—the establishment of the website www.annualcreditreport.com under FACTA—was a salient event, and consumers showed interest in free credit reports around the experiment. The examination of the Search Interest data from Google Trends supports this. *First*, the search interest for the key phrase *Free Credit Report* heightened in Jan 2005, coinciding perfectly with the establishment of the website (Panel A of Figure (V)).[7] *Second*, the plot of differential search interest across the treated and control states using the Interest-by-subregion Google Trends data suggests that consumer interest in free credit reports heightened in the treated states in the year of website's establishment. Panel B of Figure (V) shows the mean of the popularity rank for the two groups each year from 2003 to 2008. We see that the keyphrase was equally popular in both the treatment and control states in the pre-event year 2004, but it became more popular in the treatment states in 2005.[8] Also, some anecdotal evidence suggest that the website issued about 52 million credit reports to consumers in the first two years(Wikipedia, n.d.).

In this empirical strategy, it may appear to be a concern that the control group is already treated. However, a DID setting only requires that during the sample period the control group remain free from interventions that may affect the outcome of interest. Hence, the specification

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especially helpful to see a copy of your credit report before you apply for, say a car loan, a mortgage, or a credit card(Federal Reserve Bank of Philadelphia, 2015).

[6] Not only did the pre-FACTA states have higher usage of credit reports, but they also seem to have enjoyed better consumer credit environments: the rate of consumer bankruptcies was the lowest (second lowest) nationally in Vermont (Massachusetts) in 2002, and the interest rate on a conventional mortgage in Vermont and Massachusetts was below the national median (U.S. Senate. 108th Congress, 2004b).

[7] Search interest, provided by Google, is a standardized index representing the degree of searches for the keyword(s) on Google at any time relative to the highest point during the period of the analysis, over a given region(U.S. in the present case). In the time series, a value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. In the cross-section, a value of 100 represents the location with the highest popularity of the keyword as a fraction of total searches in that location. A value of 50 indicates a location that is half as popular. A score of 0 means there were not enough data for this term. Google Trends data start from January 2004.

[8] From this plot, it may appear that control states' popularity after the event decreased. However, this is the artifact of the way Google calculates this popularity measure. This is essentially a rank measure assigning ranks from 0 to 100 to states every year, 100 being the most popular. So, increase in rank of some states decreases rank of others.

in Equation (1) estimates the treatment effects as intended.

3 Data

The key data used in this paper come from the U.S. mortgage data available under the *Home Mortgage Disclosure Act of 1975* (HMDA). HMDA is the most comprehensive source of mortgages application level data in the U.S.. HMDA data provide application-level details on applicants' race and gender, income, loan amount, the financial institution handling the mortgage application, outcome of the application, and geographic location of the property at the census tract level.[9] The period of the study is from 2000 to 2008. Since the experiment occurs at the beginning of 2005, extending the sample until 2008 allows for enough post-experiment observations. The data contain 190.4 million mortgage applications over the sample period.[10]

The application-level data from HMDA are aggregated to "$CensusTract \times Year$" panel in several steps. First, all observations that have state, county or census tract information missing or "NA", or state Federal Information Processing Standard (FIPS) code as "0", "00" or "0 " are dropped (2.5% of the observations), leaving 185.6 million mortgages with an identifiable county. Then, observations on three action types are removed: the covered loan purchased by the financial institutions from other institutions (18.80%), as these are not borrower initiated; pre-approval requests denied by financial institutions (0.01%), as these data were included in HMDA reporting only from 2004; and the pre-approval requests approved by the financial institutions but not accepted by the applicants, as this data, too, were included in HMDA only from 2004, and its reporting is not mandatory (0.025%). This leaves 150.7 million applications belonging to 77,526 unique census tracts (603,849 "$Census\ Tract \times Year$" observations). Finally, Census Bureau (n.d.) data facilitate the identification of tracts belonging to the bordering counties of the treated and control states (Figure III). These 12,044 census tracts—7,054 treated and 4,990 control—constitute the final sample of 90,353 "$Census\ Tract \times Year$" observations.

Though the coverage of mortgages in the HMDA data is the largest, these lack some key application-level information, such as credit score. The data from the two GSEs—the Federal

[9] Until 2003, the census tracts in HMDA are from the Census 1990 definition, while those from the 2004 onward are from Census 2000 definition. To make the geographic area comparable across these two time-periods, I scale the census tract-level variables from 2000 to 2003 using the ratio of population residing in the 1990 definition of the census tract to that in the 2000 definition of the census tract using data from Census Bureau (2006).

[10] The sample includes mortgages for three purposes—home purchase, refinance, and home improvement, and all loan types (conventional loans, loans guaranteed by Veteran Administration (VA) and Farm Service Agency (FSA)/Rural Housing Administration (RHS), and loans insured by Federal Housing Administration (FHA)).

National Mortgage Agency (Fannie) and the Federal National Home Loan Mortgage Corporation (Freddie)—contain mortgage pricing related information including debt-to-income ratio, credit score, first-time homebuyer flag, investment purpose and more. The GSE data pertain to the 30-year fixed rate single family mortgages, the most popular mortgage type in the U.S.. Over the sample period, this data contain 33 million observations. Unfortunately, the property locations in this data are available at the coarser 3-digit zip code (henceforth, zip3) and state level. The crosswalk files provided by the U.S. Department of Housing facilitate mapping the zip3-state level information to the bordering counties included in the sample.[11] Aggregation these individual mortgages to zip3-state level yields 225 unique zip3-states and 7,711 "$Zip3\text{-}State \times Quarter$" observations.

The third important piece of data regarding the financial information of commercial banks come from "Call Reports" (FFIEC Forms 031/041). Matching the mortgage lenders in the HMDA data with the RSSD ID of commercial banks in the Call Reports requires several steps. For each mortgage application, HMDA data provide an agency code (lender's regulator) and a respondent ID, the combination of which is utilized to identify respective banks.[12] As some mortgage lenders are not banks, but the affiliates of commercial banks, they are linked using their parent entities (available in the HMDA Ultimate Panel data). If both a HMDA reporter and its parent entity yielded a successful match, the parent's match is kept. HMDA started providing RSSD ID for the reporters since 2004, so instead of agency code and respondent ID, this identifier is used for matching of data from subsequent years.

This paper relies on a few more data sources. The SCE Credit Access Survey, a triannual internet-based rotating panel survey administered since 2013 by the Federal Reserve Bank of New York, provides rich detail on consumers' credit-related expectations (FRBNY, 2013–2020). FRBNY and Equifax (n.d.) provide data on subprime population in a county. The annual survey of County Business Patterns (CBP) provides information on county-level employment Census Bureau (2000–2008). Also, the zip code level variables of CBP are mapped to census tracts level using (Missouri Census Data Center, 2010). Finally, data on state level economic conditions come from the Bureau of Economic Analysis, and population characteristics data at

[11] Areas delimited by 3-digit zip codes do not align with the county borders. Hence, to identify the 3-digit zip codes that lie along the county borders, I use the 2010 Q1 version of the 5-digit zip codes-to-county crosswalk file from Office of Policy Development and Research (n.d.). I remove all such 3-digit zip codes for which none of the underlying 5-digit zip codes lie within the bordering counties.

[12] A respondent ID equals the Federal Deposit Insurance Corporation (FDIC) Certificate ID if the lender's regulator is the FDIC and the Office of the Comptroller of the Currency (OCC) charter number if the OCC.

census-tract level are from Census 2000 (Manson, Schroeder, Van Riper, & Ruggles, 2019).

The key outcome variables of interest are the number of mortgage applications per 1000 adults in a census tract (*scaled applications*) and approval ratio. Approval ratio is the ratio of the number of successful applications (identified by action type "1" in the HMDA dataset) to the number of total applications in a census tract. Other variables of interest are the fraction of total applications denied for credit history or debt-to-income ratio and the fraction of total applications withdrawn by applicants while still under processing.

Summary Statistics

Panel A of Table (I) shows the summary statistics for the key variables over the sample period. We see that the treated census tracts have fewer scaled applications, lower mortgage approval ratio, and higher denials related to credit history and debt-to-income ratio.[13]

Panel B of Table (I) shows the comparison of the treatment and control groups in the pre-treatment period using t-test for difference in mean, the p-value for which are also shown. Results from the t-tests suggest that the control and treated census tracts differ in pre-treatment years in terms of mortgage-related variables, but are *similar* in the state- and county-level economic characteristics. The similarities in economic characteristics of treated and control areas support the comparison of outcomes across the two groups, whereas the differences in mortgage-related outcomes raise the concern that these groups may also differ on some unobserved characteristics, potentially causing an endogeneity issue. However, as a DID setting can accommodate pre-existing differences between the treatment and control subjects so long as they satisfy the *parallel-trends* assumption, the concern stands mitigated.

4 Results

This section first shows the findings on credit reports usage and discouraged borrowers. The discussion of baseline results regarding effects of free credit reports on mortgage demand, approval ratio, house prices, and default rates follows. Then, results highlighting the self-learning mechanism and the role of supply- and demand-side factors are discussed.

[13] We see that the four ratios—the approval ratio, the two denial ratios, and the withdrawal ratio—do not sum to one. There are three reasons for this. First, the reporting of the reason for denial is not mandatory under HMDA regulations; hence an application may be recorded as denied without any stated reason (70.81% of denied applications have at least one stated denial reason). Second, denial reasons could be other than credit history or debt-to-income ratio. Third, an application might be denied for multiple reasons.

§A Baseline Results

Survey evidence on the Credit Reports Usage and Discouraged Borrowers

The SCE Credit Access Survey data provide valuable insights into the credit reports/scores usage and the *discouraged borrowers* phenomenon. Given that it is a panel survey, fixed effects at "Year×month" level, together with clustering of standard errors at the same level, filter out the time trend. Also, by using as sampling weights the *weight* variable included with this survey data, we can make inference about the U.S. population.

The mean values for variables of interest are shown in Table (II). Column (1) shows that about 8% of the respondents have never checked their credit score or requested their credit reports. Column (2) suggests that staggering 20% of the respondents have either never done it, or did it at least more than two years ago (infrequent checkers). Finally, column (3) shows that about 12% of the respondents don't know their credit score.

Consumers who respond "I don't think I would get approved", defined as the *Discouraged borrowers*, are numerous as well. Column (4) shows that among those who were in the coming 12 months very/somewhat unlikely to apply for mortgage/home-based loans or refinance, or those who assigned less than 10% probability to these actions, 13% are discouraged. Further, column (5) and (6) suggest that infrequent checkers and those unaware of their credit score are, respectively, 3% and 5% more likely to report as being discouraged. Together these estimates highlight the key issue: even after more than a decade since credit reports have been free, a significant proportion of consumers: (i) do not check their reports; (ii) are unaware of their credit score; and (iii) do not apply for mortgage because they anticipate a rejection.

Mortgage demand, approval ratio and house prices

What follows next are the results on the effects of free credit report on mortgage demand (scaled applications), approval ratio, and house prices, each aggregated at the census tract level. The regression specification is in Equation (1). "$Treat \times Post$", the coefficient of interest, captures the change in the outcome variable in the treated areas relative to the control after the event. The specification includes *Census Tract* fixed effects and "$Border \times Year$" fixed effects.

Table (III) shows the regression results. Column (1) shows the regression result for scaled applications without any control variable, whereas column (2) with the controls included for local economic characteristics (annual growth rate of county income per capita, county aggregate employment, and state GDP). We see that scaled application increased in the treated tracts

by 13.3–15.4, a 13.8–16.0% increase over the pre-treatment average of 96.6. Noting that the average mortgage in these tracts in the pre-treatment period was about \$150,597, the demand increased by about \$2.0 millions per 1000 adults per census tract (\$150,597 $\times$ 13.29), by about \$5.4 millions per treated census tract (\$2 millions $\times$ 2.7 thousand adults per census tract), or, by about \$38.1 billions across the treated border counties (\$5.4 millions $\times$ 7,054 treated tracts).

Coefficients on "*Treat* $\times$ *Post*" in columns (3) and (4) estimate the effect on the approval ratio. We see that it increased by about 1–2 percentage points in the treated tracts. This represents about 5.22 more successful applications per treated tract (96.6 applications per 1000 adults in the pre-treatment period $\times$ 0.02 $\times$ 2.7 thousand adults per treated tract), about 36,827 more successful applications across the treated bordering counties (2.62 applications $\times$ 7,054 treated tracts), or a ~\$5.5 billion increase in mortgage origination across all bordering treated tracts (36,827 $\times$ \$150,597 average mortgage amount per application).

Recall that the availability of free credit reports does not affect borrowers' wealth or collateralizability of their assets. The only change it brings is that borrowers become more likely to learn their credit history and other information that lenders use to evaluate them on. Thus, the increase in approval ratio and mortgage demand point to improvements in the borrower pool likely emanating from increased self learning. Later sections rigorously reaffirm these claims.

Coefficients on "*Treat* $\times$ *Post*" in columns (5) and (6) quantify the changes in the growth rate of house prices using the house price index from Bogin, Doerner, and Larson (2016). These regressions use the census tracts level the index starting in 2000. The coefficients, though statistically significant only at the 10% level, estimate the increase in the growth rate of house prices in the treated areas relative to the control to be 1.7–1.8 percentage points after the event. Di Maggio and Kermani (2017) find a similar pattern: it increased by 3.3 percentage points following a 10% increase in mortgage origination.

Since the event occurred in the year 2005, close to the 2008 financial crisis, it is important to understand whether the increased demand came from occupancy- or investment-seeking borrowers. Panel A of Table (IV) shows the results from re-estimating the baseline regressions for only the mortgages in the owner-occupied category. These coefficients are broadly similar to those estimated for the whole sample: an increase of 12.8–14.9 (13.2–15.4%) in scaled application, and an increase of 1 percentage point in the approval ratio.

Further, regressions in Panel B of Table (IV) test for changes in the composition of demand between non-owner- and owner-occupied housing. The outcome variables are the fraction of

total mortgages that are non-owner-occupied (columns 1 and 2) and the fraction of *originated* mortgages that are non-owner-occupied (columns 3 and 4). All the coefficients suggest an increase of 1 percentage point in non-occupancy mortgages, at both the application and origination stage. Noting that about 86% of applications are for occupancy purposes, this increase is economically small, suggesting that the increase was mostly for occupancy demand.

Mortgage defaults

We saw that free credit reports resulted in higher mortgage origination. Were these consumers more, or less, likely to default? It is plausible that free credit reports led to an influx of *just-marginal* borrowers who over-borrowed and later defaulted. Another possibility is that it led to more learning among borrowers allowing them to sort themselves better in the credit market thereby improving the borrower pool, in which case defaults would decrease.

The GSE data, which contains a subset of the HMDA mortgages, allow us to compare the default rates. Default rate at a given age (measured in months since origination) and vintage year (2004 or 2005) is the ratio of mortgages that misses a scheduled payment by 30–59 days for the first time at that age to all the mortgages originated in the respective area (treated or control) and vintage year ($\text{Def}_{2004,age}$ and $\text{Def}_{2004,age}$). Adjusted default rate, defined below, then measures the differential default probability:

$$\text{Adjusted default rate}_{age} = (\text{Def}_{2005,age} - \text{Def}_{2004,age})_{treated} - (\text{Def}_{2005,age} - \text{Def}_{2004,age})_{control} \quad (2)$$

A negative adjusted default rate implies that the mortgages from the treated areas are less likely to be defaulted upon than those from the control areas at a given age. The plot of adjusted default rate with age in Figure (VII) reveals that for most of the months within six years after origination, mortgages in the treated areas were less likely to be defaulted upon than those from the control areas (mean value -0.012 percentage points, $p\text{-}value = 0.000$). This suggests that over a period of six years since origination, the mortgages originated in the event year in the treated areas were 0.012 percentage points less likely to be defaulted upon compared to the mortgage originated a year before, after accounting for the trend in the control areas. Moreover, a noteworthy pattern emerges around the 2008 financial crisis. Around the age of 48 months, which corresponds to the bust years after the financial crisis (48 months after 2005 is 2009), the adjusted default is even more negative suggesting that the performance of the treated

mortgages was superior even during and after the crisis.[14]

Overall, we learn that free credit reports stimulated the mortgage demand, raised the approval rates, and resulted in lower *ex-post* defaults, consistent with an improved borrower pool.

§B Mechanism: Consumer Self-learning Channel

The results related to the consumer *self-learning* mechanism follow next. Under this mechanism, credit reports aid consumers in better self-assessment of their creditworthiness. Before making a credit application, by relying on the information in the credit report, one can self-assess creditworthiness more accurately. If one learns from the report that creditworthiness signaled by the report would result in application approval, he or she continues with the application. Otherwise, one delays the application to take steps to improve the credit records, correct any inaccurate information therein, search for a more suitable lender (say, a sub-prime lender), or altogether abandon the application. Thus, relying on the information in the reports, learned borrowers sort themselves better in the credit market: creditworthy borrowers stay-in/enter the market, while those with bad creditworthiness may search for a sub-prime lender, or exit. This improves the quality of the applicant pool and raises the approval ratio. Besides, the demand for credit may increase or decrease depending on (i) whether, on average, consumers over- or underestimate their creditworthiness in the absence of learning their type from the reports; and (ii), the proportion of consumers who are unaware of the reports and their role in the application process. Hence, under this demand-driven mechanism, the lower economic costs of credit reports leads to its wider usage and increased self-learning among consumers of their creditworthiness, and ultimately shapes the credit demand and approval ratio.

Reduction in subprime population fraction

An implication of better self-assessment of creditworthiness among consumers is that new prime consumers may enter the market and/or some (just-) subprime consumers may become prime. Thus, the subprime population fraction in the treated counties would decrease relative to the control counties. The Equifax data on subprime (credit score $\leq$660) population fraction at the county level facilitate this analysis.

[14] It may seem counter-intuitive at first that the newly treated areas could perform even better (less default) than the nearby areas which already had free credit reports. This is plausible provided that the event brings out changes in the borrower pool in the treated areas, but not in the control areas. Improved performance in control areas is coming from improved pool in the post-event period relative to the worst pool from pre-event period, whereas in control areas, there is no improvement—(good) pool in post-event period is the same as in the pre-event period.

Panel A of Figure (VI) plots the difference between the median of the subprime population percentage across treated counties and control counties calculated yearly from 2000 to 2009. We see that before the free credit report law, subprime population in the treated counties was increasing with respect to the control counties, but one year after the event, it starts to decrease. Using mean instead of median results in a similar patter, as Panel B of Figure (VI) shows. As previously mentioned, availability of credit reports by itself do not alter financial situation or creditworthiness of consumers, unless consumers use the reports and take actions. Thus, a decrease in subprime population in the treated counties directly points to improvements in the borrower pool consistent with increased consumer self-learning.

Contraction in rejections due to credit history

If consumers learn about their credit history from their credit reports, rejections due to credit history would go down after free credit reports become available because these reports cannot affect rejections by themselves. In other words, if their creditworthiness knowledge were perfect and self-learning did not increase after the event, probability of rejection due to credit history, and due to debt-to-income ratio, would not change.

The above predictions are tested using the regression Equation (1). The outcome variables are the fraction of total applications rejected due to the respective reasons. These regressions are estimated for full sample and over a sub-sample of the census tracts that had rejection rates higher than the *regional mean* in the pre-event year 2004 (high rejection areas).[15] The rationale for testing over this sub-sample is that the areas where consumers were more often denied mortgages before the event are more likely to value the information in their reports.

Table (V) shows the results. In columns (1) through (4) we see that the fraction of applications denied due to credit history decreased by 0.3 percentage points in the treated tracts relative to the control, statistically significant only in the *ex ante* high rejection rate areas (columns 3 and 4). As mentioned before, the reason we could detect reduction only in the high-rejection areas is that consumers who had faced more rejections are more likely to value the information. Besides, we cannot estimate a reduction in rejections due to a particular reason if mortgages

[15] The steps to calculate *regional mean* are as follows. A region is defined as the area encompassing a control (pre-FACTA) state and all the surrounding states. Consider the control state Colorado (CO) and all the surrounding treatment states. Regional mean for this region is the average rejection rate for the census tracts in all the counties at the border between CO and WY, UT, AZ, NM, OK, KS and NE. Regional means of rejection rates for all seven control states are calculated in this way, and a census tract is then classified as a "High rejection tract" if its rejection rate is more than the regional mean in 2004.

are not likely to be rejected in the first place. The coefficients in columns (5) through (8) show that the debt-to-income ratio denials did not decrease. These results, despite being statistically weak, indicate that the rejection patterns changed around the event in a manner consistent with consumers learning more about their credit history.

However, these results come with a caveat. HMDA does not mandate lenders to report rejection reasons, so if their reporting incentives changed with the event, we would incorrectly attributed lender-induced change to consumer self-learning. However, it seems unlikely as lenders reported a rejection reason in over 70.81% of the rejections. Also, incentives to report rejection reasons would need to change differently in a particular manner between treated and control tracts in the event year to bias the above results, an unlikely scenario.

Confident searching (Drop in in-process application withdrawals)

In-process application withdrawals too sheds light on self-learning mechanism. Owing to uncertainty over success of their applications, and in a bid to secure better terms, consumers tend to formally initiate applications at multiple lenders and incur non-refundable application costs at each of them.[16] In the end, they finalize with one lender, the one with higher certainty and/or better terms, and withdraw from the others. About 12% of the applications over the 2000–2008 period were withdrawn while being assessed by lenders (in-process withdrawals).[17] If consumers learn their creditworthiness better under the free credit reports regime, they would be more certain over the approval probability and mortgage terms (confident applicant). Hence, they would apply at fewer lenders *ex-ante* and save the costs of multiple applications, leading to fewer withdrawn applications in aggregate.

Table (VI) shows the result of regressing fraction of mortgages withdrawn while in process, using Equation (1). The estimates show that it dropped by 0.9–0.11 percentage points in the treated tracts relative to the control. This decrease represents ~2.34 fewer in-process withdrawals per treated tract, or ~16,513 fewer withdrawn applications over the treated border counties. At an average cost of ~$400 per withdrawn application, consumers saved ~U.S. $6.6 millions in upfront charges. Moreover, this finding is not confounded by changes in incentives

[16] Credit reporting agencies do not penalize multiple applications if they are made within a short window. Equifax (n.d.) puts it this way, "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 length of this period 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."

[17] Anecdotal evidence suggest that consumers tend to withdraw application when they find a better offer from other lenders (Reddit Forum, n.d.).

of lenders around the event as withdrawals are consumer decisions, outside of lenders' control.

Increase in first-time homebuyers

As alluded to previously, about 15% of households in the U.S. do not apply for credit because they anticipate rejection (Survey of Consumer Finances, 1998–2007). While the fraction of such consumers who overestimate the rejection probability and do not apply for mortgage is unknown, changes in the fraction of applicants that are buying home for the first time can tell us if and how free credit reports affect the *discouraged borrowers* phenomenon.

The GSE data, but not the HMDA, contain information on first-time homebuyer. As mentioned in the Data section, the location of the houses in the GSE data is available only at the 3-digit zip code (zip3) and state level, so identifying those residing within the border counties of the treated and control states involves approximation (see Footnote 11). Another issue is that about 6.71% of the observations in the GSE data pertaining to the bordering counties have first-time homebuyer status missing. Hence the outcome variable—proportion of mortgages by the first-time homebuyers—is defined as the fraction of all mortgages or only the mortgages with valid first-time homebuyers information. The regression equation for this test is specified at the zip3-state level, different from the census tract-level aggregation in earlier regressions:

$$Y_{zsjt} = \beta_0 + \beta_1 \text{Treatment}_{zsj} \times \text{Post}_t + \delta \times \text{Economic controls} + \alpha_{zs} + \gamma_{jt} + \varepsilon_{zsjt} \qquad (3)$$

Here, z indexes the areas delineated by a 3-digit zip code at the border of treated state s and control state j. α_{zs} is zip3-state fixed effects. γ_{jt} is the "Border×Quarter" fixed effects, similar to that in (1). The sample is limited to the zip3-state areas that come under the border counties of treated and control states. Table (VII) show the results of this regression. Coefficients in columns (1) through (4) show that the percentage of first-time homebuyers increased by 1 percentage point in the treatment areas relative to the control areas. This increase confirms that free credit reports does mitigates the issue of *discouraged borrower* phenomenon among the first-time homebuyers, likely through improved self-learning.[18]

[18] A concern is that the mortgage sample used in this result consists of those selected by the GSEs. However, as similarly argued before, this selection would be an issue if GSEs' incentives to purchase first-time homebuyer mortgages relative to their overall purchase from the treated counties increased relative to the control in the year 2005. Such a time- and location-specific change seems improbable.

§C Is it the demand-side or supply-side factors that drive the results?

We saw that the treated areas saw increased mortgage demand and origination after the event. Increase in demand and a decrease in in-process application withdrawals indicate a demand-driven mechanism as these decisions are consumer determined and are mostly independent of lenders action. However, supply-driven increase in mortgage origination is also plausible. Recall that lenders too became aware that consumers could now get free credit reports. So, in response, they could increase the mortgage supply. In a limiting case, one may argue that the entire increase was due to lenders action, and not due to increasing demand from consumers. This section employs two set of tests—equilibrium interest rates and heterogeneity-based tests—to argue that while the role of supply-side factors may not be ruled out, the origination increased primarily due to the demand-side factors.

§C.1 Distinguishing supply and demand effect using equilibrium interest rate

In a supply-demand framework, an increase in quantity and price of a good occurs when demand curve shifts outward and the supply curve stays the same or shifts outward inadequately causing the equilibrium price to rise for the market to clear. Since previous results already show that mortgage demand increased, an increase in mortgage interest rates would confirm that the primary mechanism is demand-driven. Application-level interest rates from the GSE data allows us to examine this. The outcome variable is interest rate in percentage, and the regression specification is similar to Equation (3), but is specified at the loan level i:

$$\mathrm{Y}_{izsjt} = \beta_0 + \beta_1 \mathrm{Treatment}_{izsj} \times \mathrm{Post}_t + \delta \times \text{Economic controls} + \alpha_{zs} + \gamma_{jt} + \varepsilon_{izsjt} \qquad (4)$$

The loan-level controls include credit score, debt-to-income ratio, combined loan-to-value (loan-to-value ratio inclusive of all loans secured by a mortgaged property), number of units comprising the related mortgaged property, and percentage of mortgage insurance coverage. Table (VIII) shows the results of the regression: column (1) without any control, and column (2) with the above loan-level controls included. We see that interest rate in the treated areas increased by 0.9–1.1 basis points for a loan with similar observable characteristics, including credit score, debt-to-income-ratio and so on. This finding contradicts a supply-driven increase, but is consistent with a demand-driven mechanism.

One may wonder if the increase in interest rate is due to increase in risky borrowers in the

treated areas. This seems not to be the case as these specifications controls for applicants' credit scores. Also, we would see later in Section (5) that prime mortgages increased 30 times more than subprime mortgages in the treated areas relative to the control. A further concern is that the increase in the rates is small. Two factors plausibly contribute to this: first, the supply of mortgages in the U.S. is highly elastic because of the large-scale purchases by the GSEs of conforming mortgages in the secondary market; second, the interest rates for 30-year mortgages fluctuate little across lenders. Besides, even if the increase in interest rate were statistically non-significant, it would be valid to conclude that results are demand-driven, as interest rates would need to decrease in a statistically significant manner for results to be supply-driven.

§C.2 Distinguishing supply and demand effect using heterogeneity tests

The heterogeneity in the effects of free credit reports on demand and approval ratio may further throw light on the role of supply and demand factors. If the results were driven primarily by lenders, the effects would be heterogeneous across lenders characteristics, else across consumer characteristics. Then, the effects may vary with either set of characteristics if these are correlated. Following tests examine heterogeneity across density of lenders, and consumer creditworthiness and income.

Heterogeneous effects by density of lenders: If the increase in mortgage origination were driven by lenders, increase in mortgage origination and/or approval ratio would be greater in areas where the density of lenders is high. To examine this, a census tract is classified as having high lender density if the number of HMDA lenders per adult in the pre-event year 2004 in a census tract is more than the *regional mean* (see Footnote 15).

Table (IX) shows the results obtained from separately estimating regression Equation (1) for low and high lender density areas. Columns (1) through (4) show the results for dollar volume of mortgages originated (in 1000 USD) per adult in a census tract. $Treat \times Post$ coefficients are smaller and have weaker statistical significance for high-density areas (in specification 2 and 4) than for low-density areas (in specifications 1 and 3, respectively). Thus, high-lender-density treated areas saw smaller increase than low-lender-density treated areas after controlling for concurrent changes in the control areas with comparable lender density. t-test for the difference in the coefficient of $Treat \times Post$ in high- and low- lender-density areas ($High - Low$) shows no statistical difference. Then, columns (4) through (8) repeat the analysis with ap-

proval ratio as the outcome variable. The results are similar—there is no statistical difference in the increase in the approval ratio in areas with a high or low lender density. Overall, these findings are inconsistent with the explanation that mortgage origination and approval ratio could have increased solely due to lenders increasing the supply of mortgages.

Heterogeneous effects by creditworthiness of consumers: If credit reports aid consumers in assessing creditworthiness, and lenders approve creditworthy borrowers, effects of free credit reports should be higher in areas with *ex-ante* high fraction of creditworthy consumers. To examine this, a county is classified as having high creditworthiness if its subprime population fraction in year 1999 is less than the *regional mean* (see Footnote 15).[19]

Panel A of Table (X) shows the results obtained from separately estimating regression Equation (1) for counties with high and low creditworthiness. Columns (1) and (2) show that scaled application increased by 16.7–18.1 (17.3–18.7%), while columns (3) and (4) show that approval ratio increased by 2 percentage points in treated high-creditworthiness counties relative to control counties with similar creditworthiness. Interestingly, coefficients in columns (5) through (8) show that the increase in low-creditworthiness areas was far smaller: scaled application increased by 8.5–10.6 (8.8%–11%) and approval ratio increased by 1 percentage point, and had weaker statistical significance. These results are consistent demand-driven change in which borrowers self-learn their creditworthiness through increased credit reports usage.

Given that county-level creditworthiness measure is noisy, we can use the number of payday lenders as a more precise proxy, as they tend to operate in subprime areas (Prager, 2009) and their locations are available at the 5-digit zip code level (Census Bureau, 2000–2008). However, among the states in the sample, only Colorado and the bordering states allow unrestricted payday lending activity while others restrict it to varying degrees (Prager (2009) and Bhutta (2014)). Thus, next set of regressions use this alternative proxy, and keep only the counties at the border between CO and the surrounding treated states (WY, UT, AZ, NM, OK, KS and NE). Creditworthiness of a tract is high if the number of payday lenders in pre-event year 2004 is *less* than the mean number of payday lenders across all census tracts within these counties.

Panel B of Table (X) shows the results. Dramatic differences exist in the effect of free credit reports across high and low creditworthiness areas. Coefficients in columns (1) through (4)

[19] The choice of year 1999 follows from Mian and Sufi (2009) who suggest that such classifications should be done at a time well before the start of the housing boom as creditworthiness of an area may endogenously change with the housing boom. FRBNY and Equifax (n.d.) data on county subprime fraction start from year 1999.

suggest that compared to control high-creditworthiness areas, the scaled application increased by 68–72 and approval ratio increased by a staggering 6 percentage points in the treated high-creditworthiness areas. The coefficients in columns (5) through (8) show that the increase was smaller for scaled application, at 43, and no significant increase at all in approval ratio in treated-low-creditworthiness areas compared with similar control areas.

The finding that the effect of free credit reports varies with creditworthiness of consumers, a demand-side characteristics, corroborates a demand-driven. These results also rule out that subprime credit is the reason behind the increased origination.

Heterogeneous effects by income level of consumers: The effects of free credit reports may be heterogeneous across borrowers' income for two reasons. First, the cost of mortgage rejection is higher for low-income consumers. Second, marginal propensity to borrow is high for low-income consumers, while marginal propensity (among lenders) to lend to these consumers is low (Agarwal et al., 2018). Thus, any increase in approval ratio for the low-income consumer would strongly point to an improvement in the borrower pool rather than to an increase in lender willingness to originate disproportionately more mortgages to them. However, we cannot infer the same for high-income consumers.

Table (XI) shows the results obtained from separately estimating regression Equation (1) for each income-quartile (calculated yearly among the applications from areas in the sample). Coefficients in Panel (A) show that the scaled application increased in each quartile except the lowest, and the effect is larger as we move from the lowest quartile (column 1 and 2) to the highest (column 7 and 8). Coefficients in Panel B shows that approval ratio increased by 1 percentage point in the lowest income-quartile, and is statistically significant at the 1% level (columns 1 and 2), while it did not increase statistically significantly for the rest.

These findings are remarkable. If one were to argue that the increase in mortgage origination was supply-driven, we would observe a larger increase in the approval ratio for higher income consumers, because (i) the increase in applications was more for higher income consumers; and (ii), the propensity to lend to high-income consumers is high. Yet we see that the approval ratio increased more for low-income consumers. The preferred interpretation is that the scope of error in self-evaluation of creditworthiness and cost of rejection are higher for low-income consumers, making them more likely to benefit from accurate self-assessment. The heterogeneity in the effects of free credit reports across the income level of consumers, a

demand-side characteristics, is consistent with a demand-driven mechanism coming through the self-learning channel.

All in all, the equilibrium interest rates and three heterogeneity tests consistently point towards a consumer-driven mechanism driving the increased origination.

5 Supplementary Discussion

This section discusses the market patterns around the event that serve to rule out a few alternative mechanisms, and investigates the effect of free credit reports on commercial banks.

Did origination increase due to rise in private securitization?

An alternative explanation for increased mortgage origination is that higher commissions from private (non-government) securitization led lenders to increase the mortgage supply (Keys et al., 2010). If increased approval in the current context were due to private securitization, the fraction of originated mortgages being sold to non-government (private securitization) entities would increase in the treated areas.

Table (XII) examines the above prediction by employing Equation (1). The outcome variables are the fraction of total applications that lenders originated and (1) sold to non-government entities, (2) sold to the four GSEs (Fannie Mae, Freddie Mac, Ginnie Mae, and Farmer Mac), and (3) did not sell. Columns (1) and (2) show that there is no change (increase) in the fraction of mortgages sold to the private entities (non-GSEs), columns (3) and (4) show that the fraction of mortgages sold to the GSEs increased, and column (5) and (6) show that the fraction of unsold mortgages did not change either. Thus, there is no evidence of an increase in private securitization in the treated areas.

Did origination increase due to subprime lending? Credit score-based evidence

It may be argued that increased mortgage origination is due to an increase in the subprime credit (Mian & Sufi, 2009). Employing the comprehensive HMDA data and location-based proxies of creditworthiness, Table (X) already suggest that effect of free credit reports was stronger in the prime counties/census tracts than in the subprime. These proxies are informative and widely used (Di Maggio & Kermani, 2017; Mian & Sufi, 2009), but are imprecise. By restricting ourselves to the GSE sample, we can use precise application-level credit scores.

Table (XIII) shows the results of regressing separately the number of prime (credit score $\geq$ 620) and subprime *originated* mortgages in zip3-state areas using Equation (3). Columns (1) and (2) show that the number of prime mortgages increased by 308–312 in the treated zip3-state areas relative to similar control zip3-state areas, whereas columns (3) and (4) imply that subprime mortgages increased only by ~10 applications, which is 30 times smaller. In conclusion, the increased origination did not disproportionately go to subprime consumers. These estimates, however, are not directly comparable to the previous as the observation unit here is zip3-state, not census tracts which was the unit in the previous regressions.

These results come with the same selection issue that applied to the previous results utilizing the GSE data. Same argument as before allays this concern. In addition, before 2007 the GSEs sought to buy more subprime, not prime, mortgages to combat the housing bust (Elul, Gupta, & Musto, 2020), thus their changing incentives appears not to be a critical concern here.

Effect of free credit reports on banks

So far we focused on effect of free credit reports on borrowers. It is only natural to ask what was the effect on the banks. The empirical design of the paper, however, faces important limitations in this regard. First, commercial banks are not the dominant mortgage originators. Despite being 80% of mortgage lenders by number, banks accounted for just 37% of the mortgage lending in 2005, thus the conclusions drawn from studying banks may not be same for all lenders (Avery, Brevoort, & Canner, 2007). Second, many banks operate across states, so their treatment and control status in this natural experiment is continuous, rather than binary. The treatment intensity is proportional to bank's *ex-ante* mortgage activity in the treated and control states. Nonetheless, we can examine this question by classifying a bank as treated if in the pre-event year 2004 the ratio of mortgage it originated in control states to that in treated *and* control states combined is larger than the cross-sectional average. The regression equation is:

$$Y_{bt} = \beta_0 + \beta_1 \text{Treatment}_b \times \text{Post}_t + \delta \times \text{Bank controls}_{bt} + \alpha_l + \gamma_t + \varepsilon_{bt} \tag{5}$$

where Y_{bt} is the outcome variable (net interest margin (NIM), return on equity (RoE), and return on assets (RoA)). b indexes the banks; $Treatment$ is 1 if a bank is treated; $Post_t$ is 1 if year $\geq$ 2005; year t is year-quarter; α_i is bank fixed effects; γ_t year-quarter fixed effect; and *Bank controls*

include banks' log total assets, share of liquid assets to total assets, and cost of deposit.[20]

Regression results in Table (XIV) show that treated banks saw a 6 basis points increase in NIM (columns 1 and 2), a 0.74 percentage points increase in RoE (columns 3 and 4), and a 0.07 percentage points increase in RoA (columns 5 and 6). Therefore, keeping in mind the caveats described above, the outcomes from free credit reports were positive for banks as well.

An alternative mechanism based on information asymmetry

An alternative mechanism based on asymmetric information is plausible in which borrowers *privately know* their true creditworthiness type, but do not know what lenders know about them. Using free credit reports, borrowers learn that the information on them that lenders have is proportional to their true type. Hence, under the non-trivial search/application cost, bad borrowers self-select out. The borrower pool now improves relative to the situation in which borrowers do not know that lender has information about their true type, and optimistically expect that the information is better than what is warranted by their credit reports. Note that the improvement occurs here due to self-selecting-out by bad borrowers, but not by self-selecting-in by good borrowers as all borrowers *privately know* their true type. However, under the self-learning mechanism, borrowers themselves have imperfect information of their true type, thus both selecting-in by good borrowers selecting-out by bad borrowers contribute to pool improvement after credit reports become free.

The empirical findings are consistent primarily with the self-learning mechanism. We saw that in the treated areas both the mortgage applications and the first-time homebuyers fraction increased, not decreased. Both these findings provide evidence of selecting-in by borrowers, which is plausible only under the *self-learning* mechanism.

Another valid concern is that in assessing mortgage applications, together with the credit reports, lenders use private information such as those accumulated through relationship lending. This attenuates the effects of free credit reports. The concern is partially alleviated by the fact that lenders necessarily look at credit reports and scores when assessing borrowers.[21]

[20] NIM is the ratio of net interest income (sum of RIAD4074 and RIAD4301) to earning assets. I use the definition of earning assets from St. Louis Fred: it is the sum of RCFD0071, RCFD1350, RCFD2122, RCFD3545, RCFD1754, and RCFD1772 (https://fred.stlouisfed.org/series/USNIM). RoE is the ratio of net income (RIAD4340) to book value of equity. RoA is the ratio of net income to book value of total assets. Liquid assets is the sum of RCFD1754, RCFD1773, RCFD3545, RCFD1754, RCFD3545, and RCFD1350. Cost of deposit is the ratio of RIAD4073 to earning assets.

[21] Experian (n.d.) explains: "Not all lenders think the same way, and they may have different ways of making their decisions. But all of them will look at some key factors to help them decide. These include: information on your credit report including your credit history and public record data."

Robustness

The natural experiment utilized in this paper takes place in the year 2005, and the sample period chosen is 2000–2008 to allow for enough post-experiment observations. As the experiment is close to the financial crisis of 2008, it is crucial to ensure that the results are not caused by the unique lending environment that existed in 2007–2008. To this end, all the regressions when re-estimated by excluding the observations for years 2007 and 2008 yield similar results despite having only two post-experiment observations. These results are unreported for brevity.

6 Conclusion

A non-trivial proportion of consumers do not check their credit reports regularly, and do not know their credit scores. Various data suggest that consumers err in credit decisions in a manner consistent with them having imperfect information of their creditworthiness. Credit reports contain crucial creditworthiness information, and can aid them in credit-related decisions.

This paper examines the effect of lowering the consumers' economic cost of credit reports on the mortgage market outcomes. The enactment of the federal *Fair and Accurate Transactions Act of 2003* (FACTA) allowed all U.S. consumers to access three free credit reports annually from 2005, while seven states already had local laws permitting their residents to obtain the reports for free. The causal link is established by deploying this close-to-exogenous reduction in the cost of the reports in a difference-in-differences setting. Here, the border counties of the early-adopting states constitute the control group, and those of the surrounding states the treatment.

The key finding is that reducing consumers' economic costs of the reports improves mortgage market outcomes in a way consistent with improvements in the borrower pool, and benefits both consumers and lenders. Specifically, free credit reports resulted in an increase in mortgage demand and approval ratio, more credit to creditworthy borrowers, a reduction in defaults and subprime population proportion, more first-time homeowners, and better financial performance of lenders.

Though the findings pertain to the mortgage decisions of consumers, they broadly hold true for all consumer credit decisions when they have imperfect information of their creditworthiness. Furthermore, the causal nature of these findings implies that a policy intervention aimed at educating consumers of their creditworthiness may yield similar results.

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Figure I: A Sample Credit Report

This figure shows the summary page of a credit report obtained from the website www.annualcreditreport.com for free under the Fair and Accurate Transaction Act of 2003. The specific credit history-related details are not shown. The report contains, among other things, the details of the consumer's active accounts, debt-to-credit ratio, and an indication of the available borrowing capacity.

1. Summary

Review this summary for a quick view of key information contained in your Equifax Credit Report.

Report Date	Apr 14, 2020
Credit File Status	No fraud indicator on file
Alert Contacts	0 Records Found
Average Account Age	5 Months
Length of Credit History	8 Months
Accounts with Negative Information	0
Oldest Account	DISCOVER BANK (Opened Aug 29, 2019)
Most Recent Account	AMERICAN EXPRESS (Opened Jan 10, 2020)

Credit Accounts

Your credit report includes information about activity on your credit accounts that may affect your credit score and rating.

Account Type	Open	With Balance	Total Balance	Available	Credit Limit	Debt-to-Credit	Payment
Revolving	2	2	$606	$11,044	$11,650	5.0%	$70
Mortgage							
Installment							
Other							
Total	2	2	$606	$11,044	$11,650	5.0%	$70

Other Items

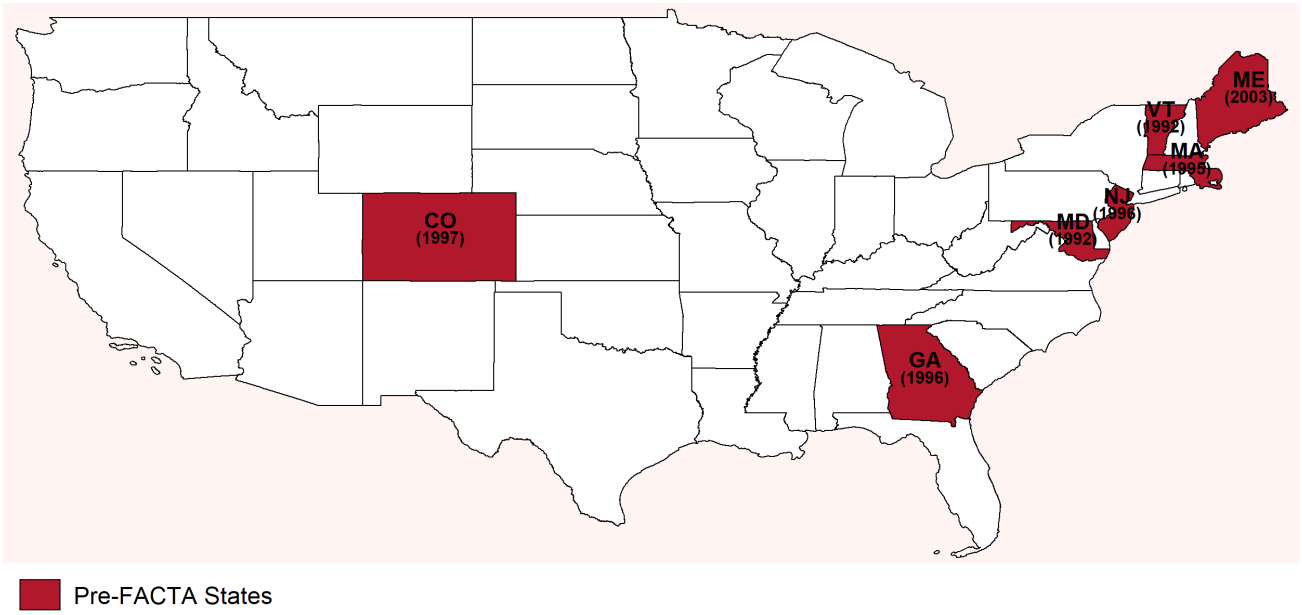
Your credit report includes your Personal Information and, if applicable, Consumer Statements, and could include other items that may affect your credit score and rating.

Consumer Statements		0 Statements Found
Personal Information		3 Items Found
Inquiries		2 Inquiries Found
Most Recent Inquiry	DISCOVER BANKAug 27, 2019	
Public Records		0 Records Found
Collections		0 Collections Found

Figure II: Differences in Access to Free Credit Reports Across US States

This figure illustrates the empirical setting of the paper. **Panel A** shows the pre-FACTA states — the states that had local laws allowing free credit reports before the enactment of FACTA in 2004 — and the respective years in which those states enacted free credit report laws. **Panel B** illustrates the difference-in-differences setting. The seven pre-FACTA states constitute the control states and the 26 states that surround them constitute the treated states.

Panel A: States Providing Free Credit Reports prior to FACTA (pre-FACTA states)



Panel B: Empirical Setting: Control and Treatment States

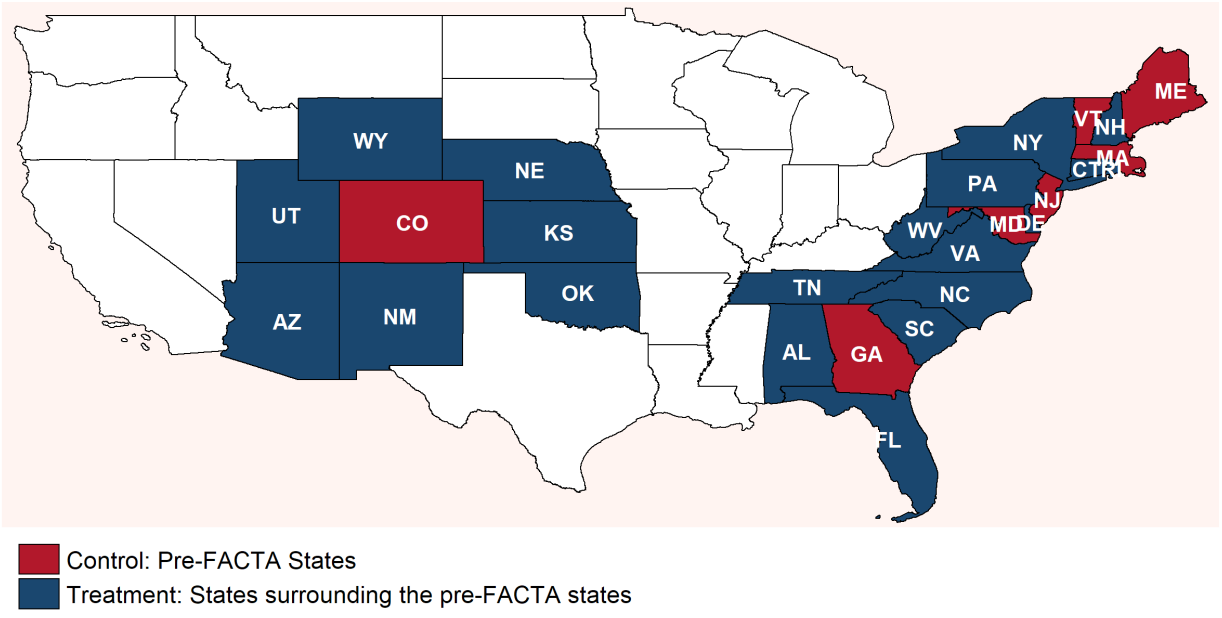


Figure III: Control and Treatment Counties

This figure shows the treatment and 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 pre-FACTA states and lying at the border between them constitute the treatment counties.

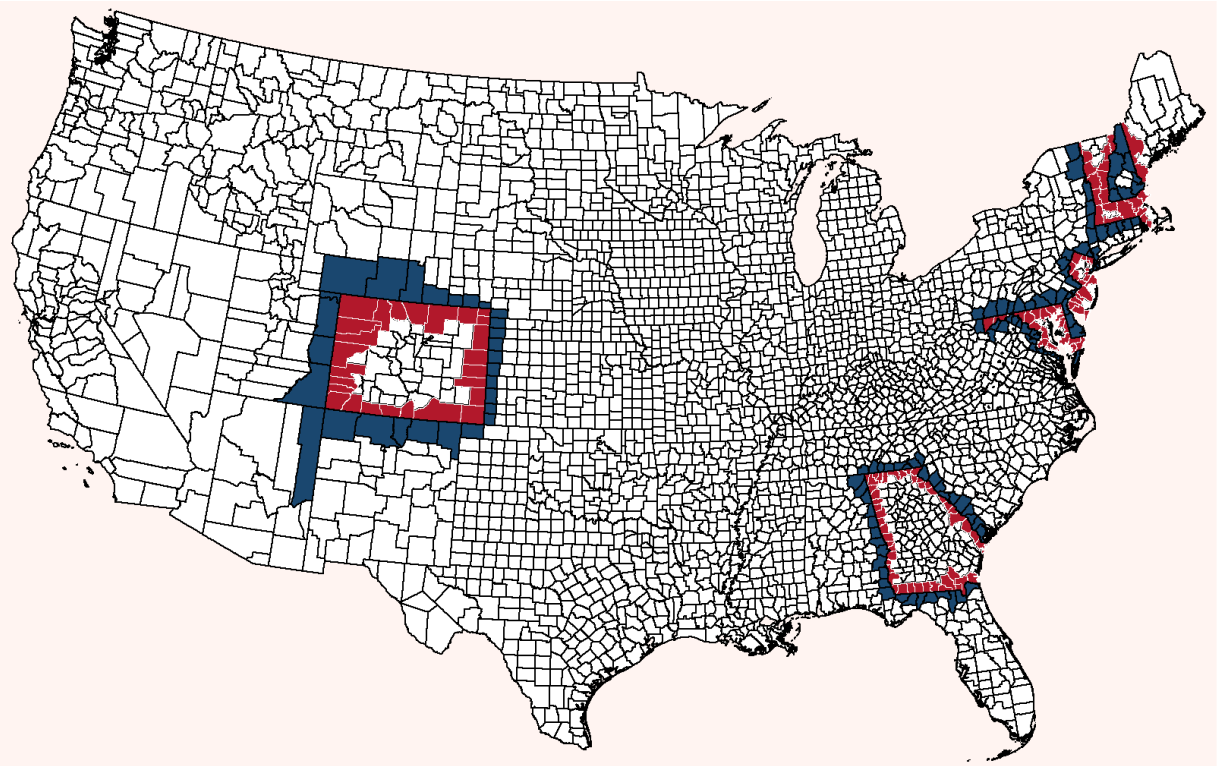


Figure IV: Examining the Parallel Trends

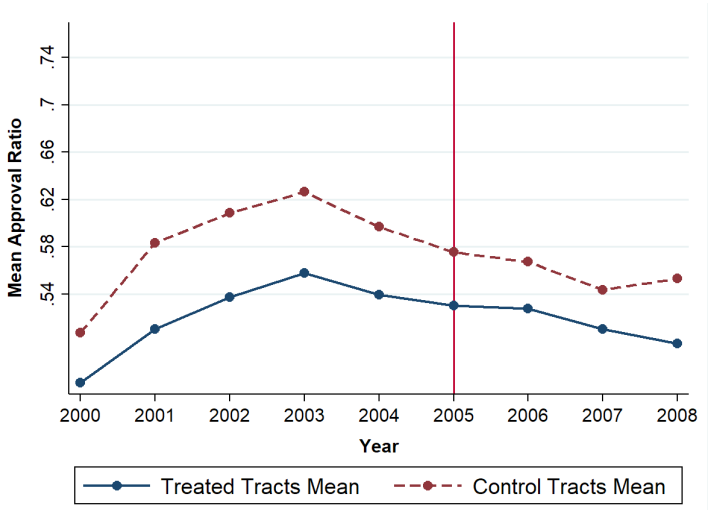
Panel A of this figure shows the mean approval ratio in the treated and control census tracts. **Panel B** of this figure shows the coefficients β_k from regressing *Approval Ratio* using the specification:

$$Y_{icsjt} = \beta_0 + \sum_{k=T-3}^{T-1} \beta_k \text{ Treatment}_{icsj} \times \text{Event}_k + \sum_{k=T+1}^{T+4} \beta_k \text{ Treatment}_{icsj} \times \text{Event}_k + \alpha_i + \gamma_{j,t} + \varepsilon_{icsjt}$$

where $\text{Event}_k = 1$ if $t = T - k$. $\text{Event}_k = 0$ if $t \neq T - k, k = \{-3, 4\}$. T = Event year 2005.

Coefficients are estimated with respect to the base year 2004 ($j = 0$). The x-axis shows year relative to the pre-event year 2004, i.e., T = +1 is the first treated year 2005. The y-axis shows the coefficients β_k. The 95% confidence interval of β_k are also shown. The regression includes "*Border* × *Year*" and "*Census Tract*" fixed effects. Other terms in the equation are the same as those in Equation 1, and are described in Section 2. Standard errors are clustered by county.

Panel A: Mean Approval Ratio in Treated and Control Areas



Panel B: Coefficient Estimates of Approval Ratio by Years to Treatment

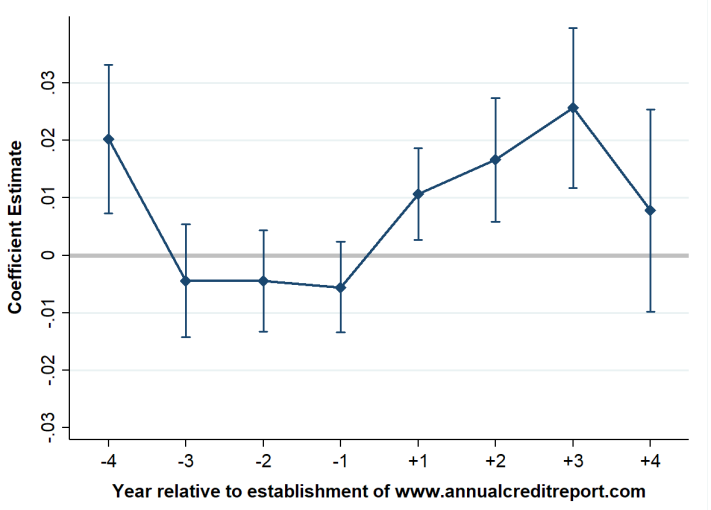
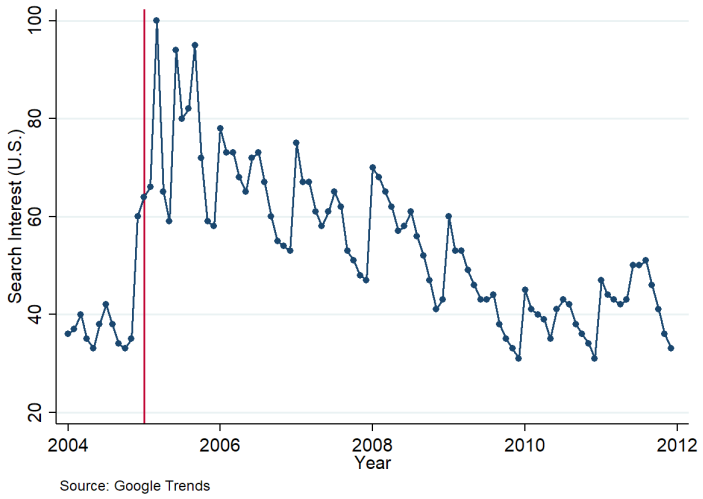


Figure V: Consumer Interest in Free Credit Reports: Google Trends

This figure shows the consumers interest in free credit report using Google Trends data. **Panel A** of this figure shows the plot of *Search Interest* for the keyphrase *Free Credit Report* in the US from Jan 1, 2004 till Dec 31, 2011. Numbers on the vertical axis represent search interest relative to the highest point on the chart during this period. A value of 100 (50) represents the peak popularity (half of the peak popularity) for the keyphrase. A value of 0 means there was not enough data. **Panel B** of this figure shows the difference in mean popularity rank of treatment and control states for the same keyphrase from 2004 to 2008. The popularity score of each state ranges from 0 to 100 and is calculated every year. A 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 where it is half as popular.

Panel A: Google Search Interest for the Term "Free Credit Report" in the U.S.



Panel B: Relative Popularity of the keyphrase *Free Credit Report*

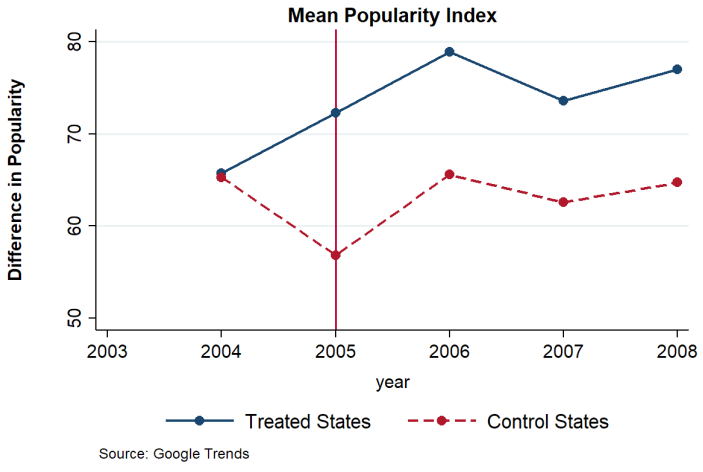
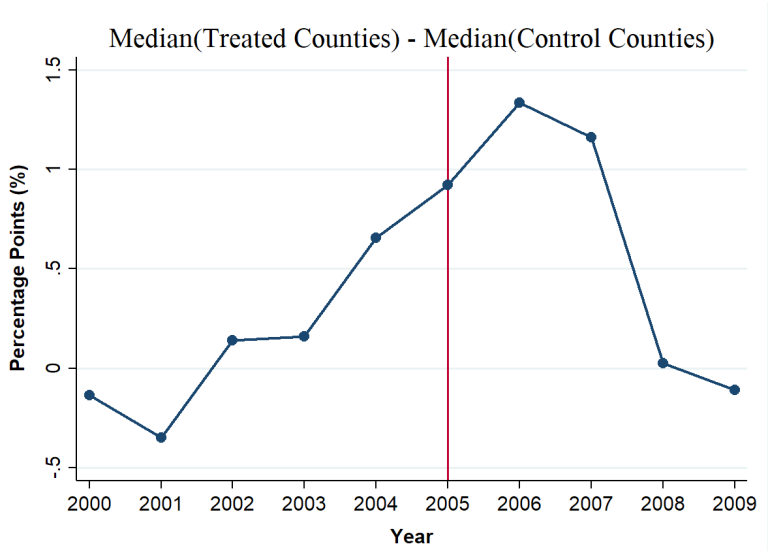


Figure VI: Subprime Population over Time

This figure plots the difference in subprime population fraction in treated and control counties. **Panel A** shows the difference in mean subprime population percentage calculated yearly over the treated counties and over the control counties. **Panel B** shows the difference in mean subprime population percentage calculated yearly over the treated counties and over the control counties.

Panel A: Difference in Subprime Population Fraction (using Median)



Panel B: Difference in Subprime Population Fraction (using Mean)

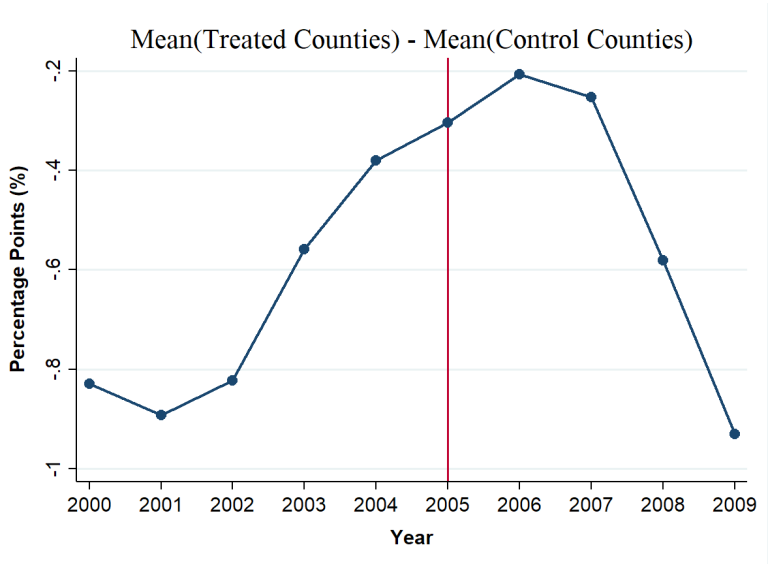


Figure VII: Effect of Free Credit Report on Mortgage Defaults

This figure shows the adjusted default rate for the sample of 30-year fixed-rate mortgages purchased by Fannie Mae and Freddie Mac. I separately calculate the percentage of total mortgages originated in the pre-event year 2004 and the post-event year 2005 which went into default in a month post-origination, $\text{Def}_{2005,age}$ and $\text{Def}_{2004,age}$, for the treated and control zip3-state areas respectively. 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:

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

where *age* represents months since origination.

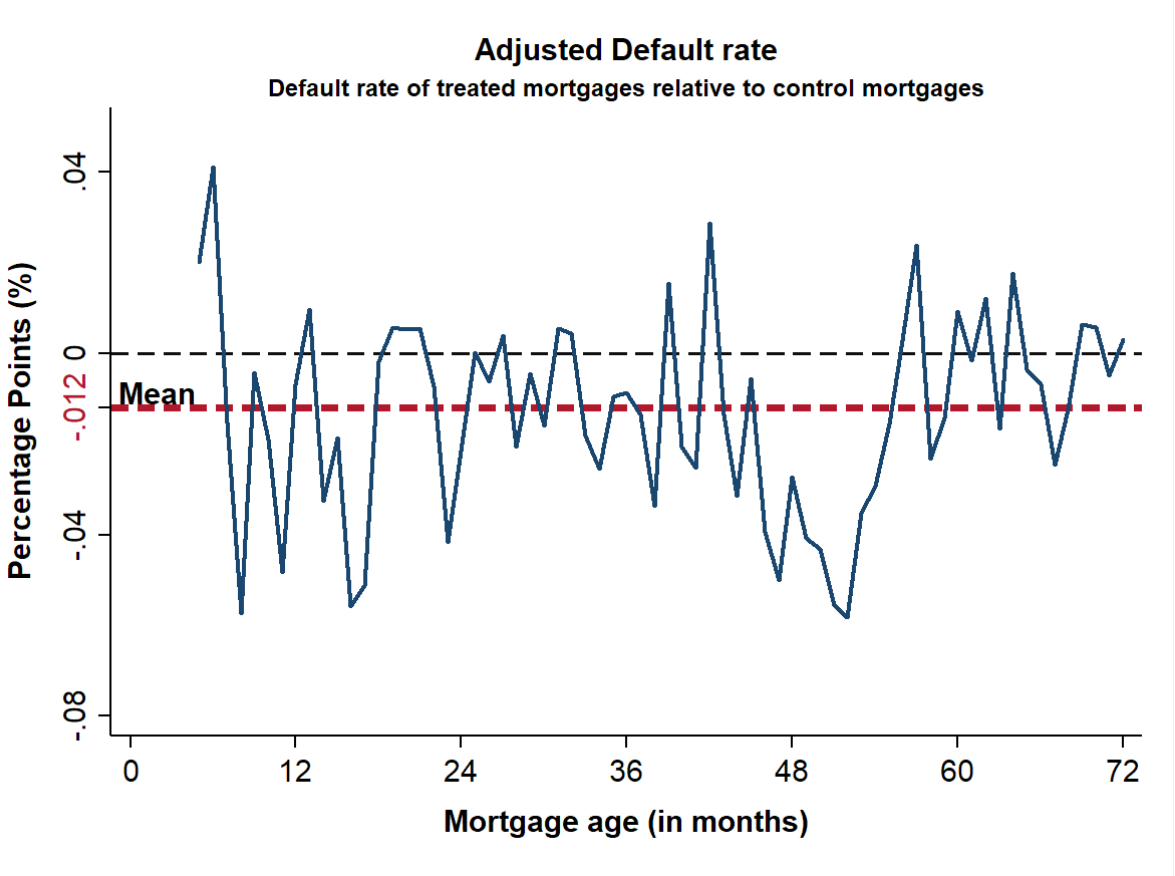


Table I: Summary Statistics

Panel A shows the statistics for the full sample time period (2000–2008). Panel B shows the statistics for the pre-treatment period (2000–2004) and the p-values for the t-test for difference in the control and treatment group. *Num of App per 1000 adults* is the number of mortgage applications scaled by the population aged 18 to 64 years 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 and debt-to-income ratio, 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 three variables at the bottom capture the economic conditions (*Economic Controls*). Δ *Inc per capita* is the annual growth rate of income per capita at the county level, Δ *Emp.* is the annual growth rate of the employment by all establishments at the county level, and Δ *State GDP* is the annual growth rate of the 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	86817	83.39	74.73	66.39	36501	98.39	77.57	77.73	50316	72.51	70.64	56.46
Approval Ratio	82712	0.54	0.13	0.55	35885	0.57	0.12	0.58	46827	0.52	0.14	0.53
Deny Credit Hist Ratio	82712	0.06	0.04	0.05	35885	0.05	0.04	0.04	46827	0.06	0.05	0.05
Deny Debt-to-inc Ratio	82712	0.03	0.03	0.03	35885	0.03	0.02	0.03	46827	0.03	0.03	0.03
Withdrawn Ratio	82712	0.12	0.05	0.12	35885	0.12	0.04	0.11	46827	0.12	0.06	0.12
Δ Inc per capita	2295	0.04	0.06	0.04	1143	0.04	0.05	0.04	1152	0.05	0.07	0.04
Δ Emp	2298	0.01	0.09	0.01	1138	0.01	0.09	0.01	1160	0.01	0.09	0.01
Δ State GDP	73	0.05	0.03	0.04	29	0.04	0.02	0.04	44	0.05	0.04	0.04

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	48363	110.48	83.53	93.48	20294	129.68	86.14	108.62	28069	96.59	78.74	83.20	0.000
Approval Ratio	47024	0.55	0.14	0.56	20077	0.58	0.13	0.60	26947	0.52	0.14	0.53	0.000
Deny Credit Hist Ratio	47024	0.06	0.04	0.05	20077	0.06	0.04	0.05	26947	0.07	0.05	0.06	0.000
Deny Debt-to-inc Ratio	47024	0.03	0.02	0.03	20077	0.03	0.02	0.03	26947	0.03	0.02	0.03	0.000
Withdrawn Ratio	47024	0.12	0.05	0.11	20077	0.12	0.04	0.11	26947	0.13	0.05	0.12	0.000
Δ Inc per capita	1275	0.04	0.06	0.04	635	0.04	0.05	0.04	640	0.04	0.07	0.04	0.614
Δ Emp	1274	0.01	0.09	0.01	632	0.01	0.09	0.01	642	0.00	0.09	0.01	0.311
Δ State GDP	41	0.05	0.02	0.05	18	0.05	0.02	0.05	23	0.05	0.02	0.06	0.795

Table II: Survey Evidence on the Credit Reports Usage and Discouraged Borrowers

This table reports the regression results from the SCE Credit Access survey. *Never* is one if a respondent has never checked his/her credit score (Q. *N23*). *Infrequently* is one if respondent has never checked it or last checked it more than 2 years ago (Q. *N23*). *Unaware* is one if respondent don't now his/her credit score (Q. *N22*). *Dscrgd* is one if respondent said "I do not think I would get approved" in *Q. N19*. Since *Q. N19* is a conditional question in the survey, and this paper concerns with only mortgage-related decisions, specifications (4–6) include only those responses in which respondent selected *very unlikely* or *somewhat unlikely* to apply for mortgage/home-based loan, or refinance in *Q. N17A*, or mentioned probability <10% in *Q. N17B* to apply for mortgage, or to refinance. All regressions include *Year* × *Month* fixed effects (FE). Standard errors are clustered by survey's Year×Month. p-values are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Check Credit Report/Score?			Mortgage-discouraged Borrowers		
	(1)	(2)	(3)	(4)	(5)	(6)
	Never	Infrequently	Unaware	Dscrgd	Dscrgd	Dscrgd
Check Infrequently					0.03**	
					(0.05)	
Unaware						0.05*
						(0.06)
Constant	0.08***	0.20***	0.12***	0.13***	0.13***	0.13***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Cluster (Year×Month)	Yes	Yes	Yes	Yes	Yes	Yes
FE (Year×Month)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.007	0.007	0.007	0.003	0.004	0.005
Observations	19231	19231	20275	9059	9058	9058

Table III: Mortgage Applications, Approval Ratio, and House Prices

This table reports the estimates of the treatment effect of free credit reports on the number of mortgage applications, approval ratio, and growth in house prices. The regression specification is:

$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}$. See Eq. (1).

N, *Aprv.*, and ΔHPI are the number of applications per 1000 adults, the approval ratio in a census tract and growth in house prices at census tract level, respectively. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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 (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	N	N	Aprv.	Aprv.	ΔHPI	ΔHPI
Treat × Post	13.28***	15.39***	0.01**	0.02***	1.74*	1.82*
	(2.94)	(3.63)	(2.42)	(2.82)	(1.83)	(1.82)
Economic Controls	No	Yes	No	Yes	No	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.807	0.808	0.748	0.744	0.683	0.686
Observations	86806	84789	82665	80667	25390	25365

Table IV: Owner-occupied Mortgages

Panel A of this table reports the estimates of the treatment effect of free credit reports on the number of mortgage applications and the approval ratio only for the sub-sample of owner-occupied mortgage applications. Panel B reports the result of regressing the ratio of not owner-occupied mortgages to total applications (to successful applications) in column 1 and 2 (in column 3 and 4). The regression specification is:

$$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}. \quad \text{See Eq. (1).}$$

#*Applications* and *Approval Ratio* are the number of applications per 1000 adults and the 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). *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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 (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Applications and Approval Ratio for Owner-occupied Mortgages

	(1)	(2)	(3)	(4)
	N	N	Aprv.	Aprv.
Treat × Post	12.78***	14.95***	0.01**	0.01***
	(2.89)	(3.61)	(2.26)	(2.60)
Economic Controls	No	Yes	No	Yes
Census Tract FE	Yes	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.808	0.810	0.661	0.654
Observations	86806	84789	86619	84602

Panel B: Non-owner-occupied Mortgages Fraction

	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**
	(1.99)	(2.03)	(2.02)	(2.13)
Economic Controls	No	Yes	No	Yes
Census Tract FE	Yes	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.088	0.087	0.087	0.086
Observations	82665	80667	82579	80581

Table V: Contraction in rejections due to credit history

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

$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}$. See Eq. (1). *%C.Hist* (*%DTI*) is calculated as the ratio of the number of denied applications due to credit history (debt-to-income ratio) 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. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). The coefficient associated with the *Treat* × *Post* interaction term captures the change in the fraction of mortgage applications denied due to a given reason 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 (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	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
	(-1.49)	(-1.51)	(-2.04)	(-1.89)	(-1.08)	(-0.96)	(-1.49)	(-1.20)
Economic Controls	No	Yes	No	Yes	No	Yes	No	Yes
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	0.538	0.575	0.575	0.267	0.266	0.319	0.322
Observations	82665	80667	39069	38692	82665	80667	39069	38692

Table VI: Confident Searching

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

$$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}. \quad \text{See Eq. (1).}$$

% Application Withdrawn is the ratio of applications expressly withdrawn by consumers to the number of applications in a census tract. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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 (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
	% Application Withdrawn	% Application Withdrawn
Treat × Post	-0.009***	-0.011***
	(-2.82)	(-3.51)
Economic Controls	No	Yes
Census Tract FE	Yes	Yes
Border × Year FE	Yes	Yes
Cluster (County)	Yes	Yes
R^2 (Adj.)	0.340	0.341
Observations	82665	80667

Table VII: Increase in First-time Homebuyers

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

$$Y_{zsjt} = \beta_0 + \beta_1 \text{Treatment}_{zsj} \times \text{Post}_t + \delta \times \text{Economic controls} + \alpha_{zs} + \gamma_{jt} + \varepsilon_{zsjt}. \quad \text{See Eq. (3).}$$

The mortgage data used in this table are from the Fannie Mae and Freddie Mac combined single-family loan dataset (GSE data). The dependent variable in column 1 (2) is the ratio of the number of first-time homebuyers to 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. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). The coefficient associated with the *Treat* × *Post* interaction term captures the change in proportion of *First-time homebuyers* in the treated 3-digit zipcode-state areas relative to the control 3 digit zipcode areas. All regressions include *Zip3-State* fixed effects (FE) and *Border* × *Quarter* FE. All variables are defined in Table (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Denominator - Applications with Known Status		Denominator - All Applications	
	(1)	(2)	(3)	(4)
	% First-time	% First-time	% First-time	% First-time
Treat × Post	0.01**	0.01**	0.01**	0.01*
	(2.55)	(2.31)	(2.00)	(1.78)
Economic Controls	No	Yes	No	Yes
Zip3-State FE	Yes	Yes	Yes	Yes
Border × Qtr FE	Yes	Yes	Yes	Yes
Cluster Zip3-State	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.691	0.692	0.691	0.691
Observations	7706	7706	7711	7711

Table VIII: Distinguishing Supply and Demand using Equilibrium Interest Rate

This table reports the estimates of the treatment effect of free credit reports on interest rates at zip3-state level geographic aggregation. The regression specification is:

$$Y_{izsjt} = \beta_0 + \beta_1 \text{Treatment}_{izsj} \times \text{Post}_t + \delta \times \text{Economic controls} + \alpha_{zs} + \gamma_{jt} + \varepsilon_{izsjt}. \quad \text{See Eq. (4).}$$

Loan Controls are *credit score, debt-to-income ratio, combined loan-to-value* $(CLTV)$*, number of units, and mortgage insurance percentage.* The coefficient associated with the $Treat \times Post$ interaction term captures the change in the dependent variable in the treated zip3-state areas relative to the control zip3-state areas. All regressions include $Zip3\text{-}State$ fixed effects and $Border \times Quarter$ fixed effects (FE). All variables are defined in Table (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Interest Rate (in percentage points)	
	(1)	(2)
	%	%
Treat × Post	0.009***	0.011***
	(13.68)	(12.60)
Loan Controls	No	Yes
Zip3-State FE	Yes	Yes
Border × Qtr FE	Yes	Yes
Cluster Zip3-State	Yes	Yes
R^2 (Adj.)	0.728	0.758
Observations	7739882	3548884

Table IX: Distinguishing Supply and Demand using Heterogeneous Effects by Density of Lenders

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

$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}$. See Eq. (1). *Low* (*High*) identifies a census tract having a 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 15). *Difference* [*High - Low*] shows the result of the t-test for the difference in coefficients of *Treat* × *Post* in specifications *High* and *Low*. The dependent variable in columns 1 through 4 is volume of mortgages originated (in 1000 USD) per adult in a census tract. The dependent variable in columns 4 through 8 is the approval ratio of mortgage applications at census tract-level. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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 variables are defined in Table (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	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	0.002**	0.001	0.002***	0.002*	0.016**	0.011*	0.017***	0.012**
	(2.20)	(1.16)	(2.87)	(1.83)	(2.52)	(1.94)	(2.87)	(2.28)
Difference [High - Low]		-0.001		-0.001		-0.005		-0.005
p-value		(0.595)		(0.600)		(0.610)		(0.592)
Economic Controls	No	No	Yes	Yes	No	No	Yes	Yes
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.)	0.643	0.571	0.633	0.563	0.758	0.728	0.754	0.723
Observations	60704	25808	59207	25293	57628	24938	56144	24429

Table X: Distinguishing Supply and Demand using Heterogeneous Effects by Consumer Creditworthiness

This table reports estimates of the treatment effect of free credit reports on the number of mortgage applications and the approval ratio in *ex ante* low and high creditworthiness areas. To separate areas by creditworthiness, Panel A uses county-level subprime population fraction, while Panel B uses census tracts-level number of payday lenders. In Panel A, a county is categorized as subprime if its subprime population fraction is more than the *regional mean* subprime population fraction in 1999. In Panel B, the classification benchmark is the average number of payday lenders in census tracts in counties at the border of Colorado (CO) and surrounding states in 2004. The sample size in panel B only includes census tracts from CO and surrounding states. The regression specification is:

$$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}. \quad \text{See Eq. (1).}$$

N and *Aprv.* are the number of applications per 1000 adults and the approval ratio in a census tract, respectively. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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 (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: County-level Creditworthiness Measure

	High Creditworthiness (Prime Counties)				Low Creditworthiness (Subprime Counties)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N	N	Aprv.	Aprv.	N	N	Aprv.	Aprv.
Treat × Post	16.74**	18.09**	0.02**	0.02**	8.49	10.63**	0.01	0.01*
	(2.30)	(2.58)	(2.31)	(2.55)	(1.65)	(2.24)	(1.58)	(1.90)
Economic Controls	No	Yes	No	Yes	No	Yes	No	Yes
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.)	0.802	0.803	0.774	0.771	0.826	0.828	0.697	0.697
Observations	39254	37692	38175	36625	47258	46808	44391	43948

Panel B: Census tract-level Creditworthiness Measure

	High Creditworthiness (# Payday Lenders - Low)				Low Creditworthiness (# Payday Lenders - High)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N	N	Aprv.	Aprv.	N	N	Aprv.	Aprv.
Treat × Post	68.43***	72.78***	0.06***	0.06***	43.72***	43.27***	0.02	0.02
	(5.31)	(5.36)	(3.52)	(3.57)	(3.82)	(4.00)	(0.94)	(0.98)
Economic Controls	No	Yes	No	Yes	No	Yes	No	Yes
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.)	0.790	0.793	0.732	0.731	0.816	0.818	0.794	0.795
Observations	1452	1452	1395	1395	872	872	865	865

Table XI: Distinguishing Supply and Demand using Heterogeneous Effects by Income Level of Consumers

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

$$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}. \quad \text{See Eq. (1).}$$

N and *Aprv.* are the number of applications per 1000 adults and the approval ratio in a census tract, respectively. Income quartiles are calculated every year for a given census tract. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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 (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A: Number of Applications per 1000 adults

	Income Quartile 1		Income quartile 2		Income Quartile 3		Income quartile 4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	N	N	N	N	N	N	N	N
Treat × Post	0.05	0.06	1.82**	2.10***	2.62**	3.06***	4.33**	5.29***
	(0.04)	(0.04)	(2.32)	(2.84)	(2.45)	(3.24)	(2.00)	(2.80)
Economic Controls	No	Yes	No	Yes	No	Yes	No	Yes
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.)	0.763	0.765	0.776	0.778	0.745	0.747	0.659	0.660
Observations	88282	86255	88282	86255	88282	86255	88282	86255

Panel B: Approval Ratio

	Income Quartile 1		Income quartile 2		Income Quartile 3		Income quartile 4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Aprv.	Aprv.	Aprv.	Aprv.	Aprv.	Aprv.	Aprv.	Aprv.
Treat × Post	0.01**	0.01**	0.01	0.01	0.01	0.01	0.01	0.01
	(2.06)	(2.59)	(0.93)	(1.03)	(0.87)	(0.89)	(1.32)	(1.27)
Economic Controls	No	Yes	No	Yes	No	Yes	No	Yes
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.)	0.344	0.346	0.391	0.388	0.404	0.399	0.363	0.357
Observations	71879	70132	72428	70661	72548	70771	71995	70219

Table XII: Did Origination Increase due to Rise in Private Securitization?

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

$$Y_{icsjt} = \beta_0 + \beta_1 \text{Treatment}_{icsj} \times \text{Post}_t + \delta \times \text{Economic Controls} + \alpha_i + \gamma_{jt} + \varepsilon_{icsjt}. \quad \text{See Eq. (1).}$$

The dependent variables are the fraction of total mortgage applications originated and sold to the non-GSEs (columns 1 and 2); originated and sold to the GSEs (columns 3 and 4); and approved and not sold by lending institutions (columns 5 and 6). The dependent variables are calculated at the census tract level. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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 variables are defined in Table (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	Sold to Non-GSE		Sold to GSE		Not Sold	
	(1)	(2)	(3)	(4)	(5)	(6)
	Fraction	Fraction	Fraction	Fraction	Fraction	Fraction
Treat × Post	-0.004	-0.001	0.047**	0.050***	0.000	0.004
	(-0.35)	(-0.10)	(2.54)	(2.76)	(0.05)	(0.94)
Economic Controls	No	Yes	No	Yes	No	Yes
Census Tract FE	Yes	Yes	Yes	Yes	Yes	Yes
Border × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (County)	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.009	0.003	0.004	0.002	0.055	0.035
Observations	82665	80667	82665	80667	82665	80667

Table XIII: Did Origination Increase due to Subprime Lending? 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 (GSEs) Fannie Mae and Freddie Mac. The regression specification is:

$$Y_{zsjt} = \beta_0 + \beta_1 \text{Treatment}_{zsj} \times \text{Post}_t + \delta \times \text{Economic controls} + \alpha_{zs} + \gamma_{jt} + \varepsilon_{zsjt}. \quad \text{See Eq. (3).}$$

The dependent variable in column 1 is *Number of mortgages originated to Prime Borrowers* (credit score≥620) in a given zip3-state area. The dependent variable in column 2 is *Number of applications to subprime borrowers* (credit score<620) in a given zip3-state area. *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). The coefficient associated with the *Treat* × *Post* interaction term captures the change in the dependent variable in the treated zip3-state areas relative to the control zip3-state areas. All regressions include *Zip3-State* fixed effects (FE) and *Border* × *Quarter* FE. All variables are defined in Table (I). Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
	N-Prime	N-Prime	N-Subprime	N-Subprime
Treat × Post	308.58***	312.51***	10.48**	10.78**
	(3.39)	(3.33)	(2.12)	(2.16)
Economic Controls	No	Yes	No	Yes
Zip3-State FE	Yes	Yes	Yes	Yes
Border × Qtr FE	Yes	Yes	Yes	Yes
Cluster Zip3-State	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.757	0.758	0.792	0.792
Observations	7711	7711	7711	7711

Table XIV: Effect of Free Credit Reports on Banks

This table reports the estimates of the treatment effect on banks. The regression specification is:

$$Y_{bt} = \beta_0 + \beta_1 \text{Treatment}_b \times \text{Post}_t + \delta \times \text{Bank Controls}_{bt} + \alpha_l + \gamma_t + \varepsilon_{bt}. \quad \text{See Eq. (5).}$$

NIM is Net Interest Margin. It is the ratio of net interest income to earning assets, expressed in percentage. *RoE* is Return on Equity. It is the ratio of net income to book value of equity, expressed in percentage. *RoA* is Return on Assest. It is the ratio of net income to book value of total assets, expressed in percentage. Bank Controls include: natural log of the total assets expressed in USD 1000; share of liquid assets in total assets, expressed in percentage; and cost of deposit (ratio of total interest expense to total earning assets, expressed in percentage). *Economic Controls* are annual growth rate of county income per capita, county aggregate employment, and state gross domestic product (GDP). 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. Standard errors are clustered by county. t-statistics are reported below the coefficients in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	NIM (%)	NIM (%)	RoE (%)	RoE (%)	RoA (%)	RoA (%)
Treat × Post	0.06***	0.06***	0.74***	0.74***	0.07***	0.07***
	(5.55)	(6.00)	(5.05)	(5.25)	(5.17)	(5.53)
Bank Controls	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster (Bank)	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (Adj.)	0.807	0.814	0.586	0.597	0.556	0.573
Observations	86323	86323	86323	86323	86323	86323