Screening Incentives and Privacy Protection in Financial Markets: A Theoretical and Empirical Analysis*

Jin-Hyuk Kim† Liad Wagman‡

Abstract

We study a model in which firms offer financial products to individuals, post prices for their products, and screen consumers who apply to purchase them. Any information obtained in the screening process may be traded to another firm selling related products. We show that firms' ability to sell consumer information can lead to lower prices, higher screening intensities, and increased social welfare. By exploiting variations in the adoption of local financial-privacy ordinances in five California Bay Area counties, we are able to provide simple estimates of the effects of stricter financial-privacy laws on mortgage denial rates during 2001–2006. Consistent with the model's predictions, denial rates for both home-purchase loans and refinancing loans decreased in counties where opt-in privacy ordinances were adopted. Moreover, estimated foreclosure start rates during the financial crisis of 2007–2008 were higher in counties where the privacy ordinance was adopted.

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†Department of Economics, University of Colorado at Boulder. Email: jinhyuk.kim@colorado.edu

‡Stuart School of Business, Illinois Institute of Technology. Part of this work was completed while visiting at Managerial Economics and Decision Sciences, Kellogg School of Management, Northwestern University. Email: lwagman@stuart.iit.edu

1 Introduction

Many financial institutions routinely collect nonpublic information about their customers to provide financial products or services.[1] When consumers apply for a loan, for instance, they provide information about their employment history and various financial statements. A lender may collect additional pieces of information from sources such as credit reports prepared by credit bureaus. Lenders and loan-servicing companies also have records of a customer's current balance, the frequency and timing of payments, and in some cases information about insurance policies obtained. Such information can be shared with affiliates or sold to outside companies (non-affiliates), including telemarketers, where it is used to better target consumers who may be interested in related products and services.

In 1999, Congress enacted the Gramm-Leach-Bliley Act (GLBA), allowing a variety of financial institutions to sell, trade, share, or give out nonpublic personal information about their customers.[2] GLBA requires financial institutions to notify consumers about how their personal information is collected and used. In particular, financial institutions that share or sell consumer data to non-affiliated third parties must give customers a chance to opt out; that is, to request that their information not be shared (15 USC §§ 6801-6809). However, there are several exemptions under the GLBA that can permit information sharing despite a consumer's objections.[3] Since the enactment of the GLBA in 1999, there has been much

[1] "Personally identifiable financial information includes all of the following: (1) Information a consumer provides to a financial institution on an application to obtain a loan, credit card, or other financial product or service. (2) Account balance information, payment history, overdraft history, and credit or debit card purchase information. (3) The fact that an individual is or has been a consumer of a financial institution or has obtained a financial product or service from a financial institution. (4) Any information about a financial institution's consumer if it is disclosed in a manner that indicates that the individual is or has been the financial institution's consumer. (5) Any information that a consumer provides to a financial institution or that a financial institution or its agent otherwise obtains in connection with collecting on a loan or servicing a loan. (6) Any personally identifiable financial information collected through an Internet cookie or an information collecting device from a Web server. (7) Information from a consumer report" (California Financial Code Sections 4050-4060).

[2] The GLBA partially repealed the Glass-Steagall Act of 1933 by allowing banking, insurance, and securities companies to operate under the same entity. Financial holding companies so created can have a variety of non-banking affiliates. Under the GLBA consumers have no right to stop sharing of nonpublic personal information among affiliates.

[3] For instance, a financial institution can share information with an outside marketer in order to jointly offer products. In fact, many of the nation's leading banks use information about their customers' shopping

debate about whether GLBA privacy provisions meet increasing public concern surrounding consumer privacy.[4]

In this paper, we explore how a firm's ability to acquire and sell consumer data influences social welfare. Existing theoretical work on privacy focuses primarily on firms' incentives to price discriminate once they acquire consumer information (see, e.g., Taylor 2004; Acquisti and Varian 2005; Calzolari and Pavan 2006; Conitzer et al. 2012). In contrast, our analysis focuses on firms' incentives to screen applicants when prices are posted upfront (e.g., Burke et al. 2012). In particular, we study a competitive industry where, prior to approving a purchase (such as a loan), sellers may work to acquire information about applicants. Such information is pertinent to sellers because it may affect the cost of rendering services and it may also be of interest to other sellers with overlapping target markets.

We investigate two settings—a confidential regime in which firms cannot sell consumer information and a disclosure regime in which information can be traded. Our paper contributes to the literature by showing that firms' ability to trade in consumer data can lead to lower prices and increased welfare when information acquisition is explicitly taken into account. Importantly, the value of information in prior work is derived from a seller's ability to price discriminate. In contrast, in our model, the value of information comes from reducing the cost of serving consumers. When the market is competitive these cost savings are passed on to consumers who benefit from significant price cuts. We show that firms' screening standards are more stringent under the disclosure regime, whereby more applicants are rejected. This is because the downstream firms' willingness to pay for consumer information rises as the accuracy of consumer information increases.

We then empirically test our model's predictions — that is, whether trade in consumer information can indeed lead to higher screening intensities and therefore to higher rejection rates. One of the main criticisms of GLBA's privacy provisions has been that most consumers

habits to help retailers target offers to customers without actually releasing their data.

[4]The 107th Congress introduced a number of bills that seek to modify the GLBA to require consumer opt-in consent for information transfers. See, for instance, the Financial Institutions Privacy Protection Act of 2001, S. 450, § 3 (2001); Consumer's Right to Financial Privacy Act, H.R. 2720, § 2 (2001).

do not (and likely will not) take advantage of the *opt-out* option to cease trade of their information.[5] In 2002, three out of five counties in the San Francisco-Oakland-Fremont (SFOF), CA, Metropolitan Statistical Area (MSA) adopted a local ordinance (effective January 1, 2003) that was more protective than previous practices by pursuing an *opt-in* approach. Specifically, the local ordinance would require financial institutions to seek a written waiver before sharing consumer information with both affiliates and non-affiliates.[6]

The California Constitution allows a county or city to make and enforce within its limits all local, police, sanitary, and other ordinances and regulations that do not conflict with the state's own general laws. That is, an ordinance is a local law adopted with all the legal formalities of a statute. Further, the privacy ordinance applied to all 'financial institutions' that engaged in financial activities (as described in 12 USC §§ 1843) and conducted business in the county. Thus, regardless of the institutional type (e.g., regulatory agency or charter status) or its size, any institution that is significantly engaged in financial activities had an obligation to abide by the local ordinance, creating policy variation across counties until it was superseded by the California state law (effective July 1, 2004), which provided the consumer financial-information privacy the local governments had sought.

We analyze Census tract-level and individual loan-level data on mortgage applications for conventional home purchase, as well as refinancing, in the SFOF MSA during 2001–2006. Comparisons of loan denial rates before, during, and after the adoption of local ordinance offer a unique opportunity for evaluating the effects of strengthening consumer financial privacy protection. Our findings are robust and new to the literature. We show that the opt-in ordinance had a statistically significant negative effect on loan denial rates (that is, approval rates increased), consistent with our model's predictions, where the effects are particularly strong for non-conforming loans. Further, we provide suggestive evidence that

[5]Critics argue that this may be the case because disclosures are often buried in fine print with confusing terminology and because the default option is for information trade to take place since consumers need to opt out (see, e.g., Johnson and Goldstein, 2004).

[6]The Association of Bay Area Governments encouraged consistency and uniformity of the local privacy ordinances, which led to a model ordinance (see `http://www.abag.ca.gov/privacy/ordinances.html`).

foreclosure start rates during the financial crisis of 2007–2008 were higher in the counties that adopted the privacy ordinance.

The paper proceeds as follows. Section 2 provides a brief discussion of related literature. Section 3 presents our basic model of consumer screening and information trade. Section 4 derives the positive and normative implications of consumer privacy protection in our model. Section 5 provides background information on state and local privacy laws and describes the data set. Section 6 presents our main empirical findings. Section 7 concludes.

2 Related Literature

This paper is related to the growing literature on consumer privacy. Taylor (2004) and Villas-Boas (2004) show that in the presence of strategic consumers, a firm may be worse off by targeting prices based on consumers' purchase histories.[7] That is, once consumers anticipate future prices, they may choose to forgo purchases today to avoid being identified as past customers tomorrow and thus have access to lower prices targeted at new customers. This strategic waiting by consumers can lower a seller's profit by reducing sales and diminishing the benefit of price discrimination. Our analysis differs from these studies in that our focus is on a competitive market where consumers apply to purchase from firms and firms decide whether to move forward with a transaction.

The literature has considered the relationship between information revelation to a potential trading partner and the efficiency of outcomes. In a sequential agency model, Calzolari and Pavan (2006) show that committing ex ante to disclose information can sometimes increase social welfare.[8] In their model, a principal can learn an agent's private information through a screening mechanism and the benefit of disclosure arises from profitably selling

[7]Other theoretical papers that investigate price discrimination based on consumer information include Acquisti and Varian (2005), Armstrong (2006), Hermalin and Katz (2006), Chen and Zhang (2009), Conitzer et al. (2012), and Taylor and Wagman (2014). See Fudenberg and Villas-Boas (2006) and Hui and Png (2006) for surveys of this literature.

[8]Their result is reminiscent of the traditional Chicago School argument that privacy protections hinder information flows that would otherwise lead to improved efficiency in the market because individuals may then misrepresent their personal information (see, e.g., Stigler 1980; Posner 1981).

information. Although our efficiency results are similar to their findings, the difference is that in their work information acquisition is modeled as a passive process that produces soft information, whereas in this paper, screening intensity is endogenously determined and it produces hard information.

Recently, researchers have begun to evaluate empirically the effects of privacy regulations. Using variation in state medical privacy laws, Miller and Tucker (2009, 2011) show that privacy regulations restricting a hospital's release of patient information significantly reduce the adoption of electronic medical records, while a 10 percent increase in the adoption of such systems can reduce infant mortality by 16 deaths per 100,000 births.[9] Goldfarb and Tucker (2011) examine the effects of the implementation of the EU Privacy Directive and find some evidence that after the Privacy Directive was passed, advertising effectiveness decreased significantly. We provide new evidence on the effects of privacy regulation with a focus on financial markets.

This paper is also related to the literature on information sharing in credit markets. Pagano and Jappelli (1993, 2002) predict that if banks share information about their customers, they would increase lending to safe borrowers, thereby decreasing default rates. Existing empirical studies mostly focus on the effects of credit bureaus and creditor rights using data from a cross-section of countries (see, e.g., Djankov et al. 2007; Qian and Strahan 2007). Recently, Hertzberg et al. (2011) and Doblas-Madrid and Minetti (2013) analyze micro data to show that the effect of lenders' information sharing is to reduce incidence of delinquencies and defaults, but lenders may reduce credit in anticipation of other lenders' reaction to negative news.

A number of papers have studied the US mortgage-default crisis and pointed out the expansion in mortgage credit to subprime borrowers (e.g., Mian and Sufi 2009). However, this literature has not explicitly considered the effects of privacy protection or privacy legis-

[9]Another growing policy issue in the healthcare market is the insurer's access to information about a person's genetic test results and subsequent price discrimination. In the US, most states have banned the use of genetic information by health insurers; however, some theoretical results show that inefficiencies may arise when test information is private relative to when it is public (see, e.g., Hoel and Iversen 2002).

lation. While acknowledging the importance of potentially confounding factors, we test our model's theoretical predictions using simple difference-in-difference models and also check the robustness of our results using loan-level control variables. The results in this paper give rise to the conjecture that privacy acts may have played some role in the subprime mortgage crisis by weakening lenders' incentives to screen loan applications.

3 Consumer Screening and Information Trade

3.1 The Model

The supply side of the market is composed of two types of symmetric firms, A and B. Firms of type A offer financial products such as conventional home loans (good A), and firms of type B offer related products, such as personal credit lines and insurance policies (good B). All firms are risk neutral and maximize expected profits. The demand side of the market consists of a continuum of ex-ante identical individuals with measure $M > 1$. A fraction of this mass, normalized to 1, is applying to purchase a loan from firm A. Individuals are assumed to be risk neutral and have unit demands (separately) for goods A and B. Let v_A and v_B denote the incremental utilities from consuming one unit of good A and B, respectively.

Suppose that there is uncertainty about cost-relevant consumer characteristics. Specifically, the cost of serving a consumer either turns out to be low (c_L^m) or high (c_H^m), with $c_L^m < c_H^m$ for $m \in \{A, B\}$. For technical simplicity, we assume that consumer types for firm B's products are perfectly correlated with those of firm A's.[10] We assume that $c_L^m < v_m < c_H^m$ for $m \in \{A, B\}$; that is for both goods, it is efficient to serve only low-cost consumers. However, if screening is imperfect, firms may end up approving some high-cost consumers. It is common knowledge that the proportion of high-cost consumers in the population is $\lambda > 0$. At the onset, information is incomplete and symmetric, and, in particular, consumers and

[10]Calzolari and Pavan (2006) make an analogous assumption. Taylor (2004) considers imperfect correlation. Incorporating imperfect correlation would not change our qualitative results but it would complicate the exposition without a major gain in intuition.

firms do not observe the realization of their types.[11]

The game unfolds in several stages. First, each firm j of type A announces a price, $p_{j,A} \in \mathbb{R}_+$, at which it will sell the good to a consumer whose application is ultimately approved. Price announcements are made publicly and simultaneously. Next, each consumer applies to purchase the good from a firm A of his choice. Then, each firm of type A acquires information about its applicants and chooses which applicants to qualify. After selling to qualified applicants, each firm of type A makes a take-it-or-leave-it offer to a firm B for purchasing its list of applicants and the information it acquired about them, including whether they were approved.[12] Finally, firm B decides whether to accept or reject this offer and proceeds to make targeted sale offers to potential customers.

3.2 Information Acquisition

A firm A chooses a sample size, or search intensity $n \geq 0$, which we treat for simplicity as a continuous variable. The cost to the firm of acquiring information about an applicant is kn, where $k > 0$. By choosing a search intensity n, firm A receives n conditionally independent Bernoulli signals, $\{X_1, \ldots, X_n\}$, where

$$\Pr\{X_i = 1 | c^A\} = \begin{cases} 1, & \text{if } c^A = c^A_L, \\ 1-\alpha, & \text{if } c^A = c^A_H \end{cases}$$

The parameter $\alpha \in (0, 1)$ represents intrinsic signal strength. If $\alpha = 1$, then a signal is fully informative, and if $\alpha = 0$, then signals contain no information. This process is interpreted as follows: A firm A chooses a search report containing $i = 1, \ldots, n$ records, $\{X_1, \ldots, X_n\}$, for each of its applicants, and each record is either positive ($X_i = 1$) or negative ($X_i = 0$).

[11] When consumers' cost types are privately known by consumers at the beginning of the game, our main results continue to hold as part of a pooling equilibrium, provided that $v_A - v_B$ is sufficiently high, whereby a type c_H consumer would not forgo applying to purchase good A in fear of not being offered good B.

[12] Selling to a single firm of type B is not restrictive. As we will show below, the value of information is derived from updating beliefs about a consumer's cost type, so that a firm A can indeed sell to multiple firms of type B. An alternative interpretation is that the aggregate measure of B firms is normalized to one.

Since the firm is in effect searching for bad news about its applicants' creditworthiness, it is possible to summarize all the information contained in an applicant's search report with the sufficient statistic $S_n \equiv \min\{X_1, \ldots, X_n\}$. That is, if $S_n = 0$, then at least one of the records was negative, and the applicant (referred to as disqualified) is certainly type c_H^A; whereas if $S_n = 1$, then all records were positive, and the applicant (referred to as qualified) is type c_H^A with probability

$$\mu(n) = \frac{\lambda(1-\alpha)^n}{\lambda(1-\alpha)^n + (1-\lambda)} < \lambda \tag{1}$$

and type c_L^A with the complementary probability $1 - \mu(n)$.

After acquiring information about a consumer, a firm j of type A decides whether to approve the consumer's application (i.e., sell him the good at its posted price $p_{j,A}$). Approval results in an expected payoff of $p_{j,A} - E[c^A|S_n] - kn$ for the firm. Rejection results in a payoff of zero for the consumer and $-kn$ for the firm. We define a measure of the efficacy of firm A's information-acquisition technology as follows:

$$m \equiv -\frac{k}{\ln(1-\alpha)}.$$

Lower values of m correspond to better technologies involving low sampling costs and/or a high intrinsic signal strength.[13]

3.3 The Value of Information

To focus on the effects of information trade, we assume that firms of type B do not possess the technology to independently acquire information about potential customers. This is consistent with the observation that credit card and insurance policies are often approved without pursuing high levels of direct screening. Moreover, issuers often make pre-screened offers based on summary information (e.g., credit scores) that they purchase from primary

[13]The logarithm term is due to differentiating the probability $(1-\alpha)^n$ with respect to n.

sources. Let us suppose that a firm of type B (henceforth, firm B) randomly targets a fraction of the total mass of potential consumers, M. Let ξ denote the probability that a customer in firm B's initial target set overlaps with a firm of type A's approved set of applicants.

The benefit to firm B of learning about a *qualified* consumer from A's list is the following: With probability ξ, this consumer is already targeted by firm B, whereby B's benefit is zero. With probability $1-\xi$, this consumer would not have been targeted by B, in which case B's benefit is $E[c^B] - E[c^B|S_n = 1]$ in expected cost savings (where $E[c^B] = \lambda c_H^B + (1-\lambda)c_L^B$ and $E[c^B|S_n = 1] = \mu(n)c_H^B + (1-\mu(n))c_L^B$). Thus, firm B's overall expected benefit from learning about a qualified consumer is $(1-\xi)(E[c^B] - E[c^B|S_n = 1])$. Analogously, firm B's expected benefit from learning about a randomly-selected *disqualified* consumer is given by $\xi(c_H^B - E[c^B])$. Formally, we can derive B's willingness to pay per application contained in firm A's applicant list (given a level of screening intensity n) as follows:[14]

$$\underbrace{[(1-\lambda)+\lambda(1-\alpha)^n](1-\xi)(E[c^B]-E[c^B|S_n=1])}_{\text{Qualified consumer information}} + \underbrace{\big(1-[(1-\lambda)+\lambda(1-\alpha)^n]\big)\xi(c_H^B-E[c^B])}_{\text{Disqualified consumer information}}.$$

Substituting for $\mu(n)$ from (1) and simplifying yields

$$(1-\lambda)\lambda(1-(1-\alpha)^n)(c_H^B - c_L^B). \tag{2}$$

From the expression in (2), it is clear that firm B's expected benefit from information about firm A's applicant list is independent of ξ and is increasing in n. Intuitively, firm B benefits from firm A's information by being able to fine-tune its target customer set. Specifically, a higher screening intensity enables B to more effectively avoid high-cost consumers and to better target low-cost consumers. Since the overall benefit is a combination of im-

[14] Firm B could directly swap out a disqualified consumer and swap in a qualified consumer. This would generate the same expected benefit as when firm B swaps out a disqualified consumer with a new consumer (for whom it has no information), and swaps out a consumer for whom it has no information with a qualified consumer from outside its simple.

proving the targeting of individual consumers both in and out of B's initial target set, it is independent of the likelihood that A's information directly overlaps with this initial set.

4 Equilibrium in a Competitive Market

4.1 Main Results

In the following analysis, we assume that the information-acquisition technology for firms of type A is sufficiently effective (i.e., m is sufficiently small) so that an interior solution obtains with positive screening intensity (i.e., $n^* > 0$).[15] The super- and sub-scripts T and NT denote cases with and without information trade, respectively. For notational simplicity, we omit the subscript j when referring to a representative firm of type A. Lemma 1 derives a preliminary result that hold in equilibrium both when information trade is permitted and when it is not (all proofs are provided in the Appendix).

Lemma 1 *In a symmetric equilibrium, a consumer's expected utility is decreasing in firm A's price, p_A.*

Lemma 1 states that, taking into account a firm A's subsequent choice of screening intensity, an applicant's expected utility decreases monotonically in firm A's posted price. It follows that consumers choose to apply to a firm A that posts the lowest price. As the next result indicates, this choice has an important implication for a firm's level of consumer screening. In particular, the firms that post the lowest prices are also those that will be screening consumers most intensely. Our first result is the following:

[15] A condition sufficient to guarantee this is that $m < \lambda(c_H^A - v_A)$. This follows given that a firm A's expected profit without information trade is $(\lambda(1-\alpha)^n + (1-\lambda))p_A - (1-\lambda)c_L^A - \lambda(1-\alpha)^n c_H^A - kn$ and that its derivative evaluated at $n = 0$ has to be positive. The condition for an interior solution with information trade is weaker. See the proof of Lemma 1.

Proposition 1 *With information trade, (i) consumers purchase from a firm A at lower prices, (ii) more information is collected about consumers, and (iii) more consumers are disqualified from purchasing good A relative to when consumer information cannot be traded*

Proposition 1 points to an inverse relationship between price and screening intensity. From the standpoint of firms, price competition dissipates profits from selling good A. However, once information trade is permitted, firms A are able to lower their prices even further due to profits from selling applicants' information. This price reduction is coupled with a stricter screening of applicants. On the one hand, consumers benefit from lower posted prices; on the other hand, more consumers are disqualified compared to the case where information trade is prohibited. Our next result addresses allocative efficiency:

Proposition 2 *There exists a constant $\bar{c} > 0$, such that for $c_H^B - c_L^B \geq \bar{c}$, allowing for information trade strictly increases ex-ante social welfare.*

That is, when firm B's benefit from applicant information for product A is significant, the price reductions consumers enjoy ex ante for good A offset consumers' disutility from higher rates of ex-post rejections. If $c_H^B - c_L^B$ is sufficiently high, qualified consumers can even be paid to purchase good A; that is, the price for good A when information trade is permitted, $p^*_{A,T}$, could be negative. Intuitively, price commitments, whereby screening is conducted after consumers apply, lead firms selling good A to compete away their downstream profits from selling their applicants' information. In turn, more consumer data is collected and traded, more consumers are rejected from buying good A, but those who are ultimately approved enjoy significant discounts.

While our model purposely focuses on the effects of information trade in the presence of price commitments, our results provide a complementary view to those in the literature on price discrimination. In particular, the literature on price discrimination (e.g., Taylor 2004; Villas-Boas 2004; Acquisti and Varian 2005) suggests that when firm B is able to price discriminate based on information that correlates with high valuation for its products, for instance, consumers may choose to strategically avoid buying good A in an effort not to experience a price hike for good B. Here, we have shown that any such adverse effects due to price discrimination may be offset, and possibly dominated, by consumers' benefit from significant price cuts due to information trade when the market is competitive.

While we think that the above cost condition is more likely to be satisfied than not, we note that the above welfare statement is ambiguous depending on the cost-saving condition for downstream firms. Further, there are factors not considered in our model that may lead to a reduction in social welfare under information sharing. For instance, consumers may incur a direct utility cost when their nonpublic personal information is traded or shared (Daughety and Reinganum 2010).[16] While such privacy concerns alone may not deter consumers from applying for financial products, the above welfare result needs to be interpreted with caution. Also, if the market is not perfectly competitive, then there may be some strategic incentives and product differentiation on the part of screening firms.

4.2 Disutility from Default Risks

Thus far, we have assumed that consumers differ only in terms of sellers' costs of serving their respective types, where all consumers derive the same utilities from acquiring sellers' products. However, consumers' tastes may differ, whereby each consumer type derives a different value v_A from purchasing good A. For example, net utility from a loan may reflect a consumer's likelihood of default, where high-cost consumers are more likely to experience disutility from meeting mortgage payments and risk default incurring additional costs. That is, let $v_{A,H}$ and $v_{A,L}$ denote a high and low type's incremental utility, respectively. It may be the case that $v_A = v_{A,H} = v_{A,L}$ (as in the base model) no longer holds. Our analysis readily extends to the case in which high-cost consumers experience a higher level of expected

[16]Another example is one where firms of type A have different pre-existing information about consumers (e.g., due to prior relationships). Firms of type A may choose to trade consumer information with one another, in addition to trading information with firms of type B, which could end up hurting consumers.

disutility from default (and thus place a lower valuation on good A) than low-cost consumers, that is, $v_{A,H} < v_{A,L}$.

Proposition 3 *Suppose high-cost consumers derive a lower utility from good A than low-cost consumers. Then, allowing for information trade leads to higher ex-ante social welfare.*

Proposition 3 extends our findings in the baseline case by showing that information trade brings the outcome closer to the social planner's solution when taking into account high-cost consumers' higher likelihood of (and hence disutility from) default. In such cases, allowing for information trade is even more important in terms of improving welfare. This is because the social cost of misallocating good A (that is, of mistakenly qualifying high-cost consumers) is now strictly higher. Since firms screen applicants more intensely when information trade is permitted, allocative efficiency improves due to a greater likelihood of avoiding more costly defaults. In other words, when factoring in consumers' disutilities from default, there are greater benefits associated with information trade.

5 Data and Background

5.1 Privacy Legislation

Our theory predicts different levels of screening (and hence approval or rejection rates) depending on whether consumer information can be traded. As previously mentioned, the GLBA's privacy provisions place the burden on individuals to protect their privacy with an opt-out standard. That is, financial institutions can share customers' nonpublic personal information if customers neglect to respond.[17] Since the enactment of the GLBA, there have been considerable legislative activities in state governments in regards to privacy issues, financial privacy in particular. Some activities pertain to the adoption of an opt-in

[17] More specifically, consumers have no opt-out rights whatsoever against affiliate sharing, and financial institutions can further evade opt-out requirements by exploiting the exceptions in the GLBA.

standard.[18] As a result, there exists significant state-level variation in the protection and trade of consumers' financial information by financial institutions.

However, certain features of state privacy legislations render themselves less suitable for an empirical analysis exploiting state-level policy variation. First, some states, including Alaska, Connecticut, Illinois, North Dakota, and Vermont, have strict laws that currently require opt-in consent for the sharing of consumer information with unaffiliated third parties while most other states do not. The problem is that these states adopted an opt-in approach in their state banking laws long before the GLBA was enacted in 1999. Therefore, given that our data are available from 1999, pre-treatment outcomes would not be observed in these states.

Second, an increasing number of states have enacted laws that limit the sale of personal information by financial institutions and impose stricter requirements for many third-party uses. Perhaps the best-known example is the California Financial Information Privacy Act (CalFIPA), which in part superseded the opt-out approach of the GLBA.[19] Here, the main issue is that there is substantial heterogeneity in the language (e.g., definitions, scope, and strength) of state privacy laws. For instance, some state privacy laws apply only to banks and credit unions, and others pertain only to account services and electronic-funds transfers. Thus, we think that the use of state variation is more likely to suffer from pre-trends and omitted variables than within-state variation.

We focus on local government legislation where heterogeneity may be more plausibly controlled by the inclusion of observed characteristics. Before the CalFIPA was signed into law in September 2003, the bill had been rejected multiple times by the Assembly. As these bills

[18] The GLBA permits states to formulate privacy protections that exceed federal law. The Federal Trade Commission (FTC) was granted sole authority to make determinations as to whether state statutes are inconsistent with (and therefore pre-empted by) the GLBA. In 2001 and 2004, the FTC issued a formal letter in which it determined that affirmative opt-in provisions in Illinois and North Dakota, respectively, were consistent with GLBA.

[19] The opt-out provision of the CalFIPA regarding affiliate sharing was preempted by the Fair Credit Reporting Act (American Bankers Association v. Gould, 412 F.3d 1081). However, in 2008 the Ninth Circuit revived part of the California's law regarding affiliate sharing (American Bankers Association v. Lockyer, No. 05-17163), and the Supreme Court denied review in 2009.

were being defeated, local governments in the Bay Area led efforts to strengthen consumer financial-privacy protection. In August 2002, they began enacting ordinances that would require financial institutions to obtain consumer permission before releasing their financial information to a non-affiliated third party or affiliate.[20] To our knowledge, this provides a unique event where local jurisdictions successfully implemented a consumer financial-privacy ordinance.

According to the Association of Bay Area Governments, the five counties in the San Francisco-Oakland-Fremont MSA considered adoption of such opt-in privacy ordinances. Three of them (Alameda, Contra Costa, and San Mateo) adopted the ordinance, while the other two (Marin and San Francisco) did not (see Figure 1 for a map of this MSA). It is difficult to rule out the bias introduced by endogenous policy adoption. However, we believe that it is reasonable to assume that the adoption was related to the financial industry's lobbying and/or to job-related issues near central cities rather than being systematically associated with loan application outcomes.

We chose 2001 and 2002 for our pre-intervention period because the GLBA came into effect on November 13, 2000, facilitating the sharing of consumer information among affiliates by establishing an opt-out standard and allowing different types of companies to affiliate with each other via a holding company. The Bay Area local ordinance was adopted on October, 2002, with an effective date of January 1, 2003. However, CalFIPA, which established statewide opt-in requirements, went into effect on July 1, 2004, eliminating the policy variation created by the (non)adoption of the local privacy ordinance across the five counties. Hence, our main intervention period is 2003 and 2004 (before CalFIPA), and the post-intervention period is 2005 and 2006 (after CalFIPA).[21]

[20]Similar to the case of CalFIPA, in response to a lawsuit filed by Bank of America and Wells Fargo, a federal judge struck down the local ordinance with regards to affiliate sharing on July 29, 2003, but the restriction on non-affiliated third-party sharing (unless a consumer gives advance consent) was upheld.

[21]Both the local ordinance and the CalFIPA were in part pre-empted by the affiliate-marketing provisions in Section 214 of the Fair and Accurate Credit Transactions Act of 2003. However, the Federal Trade Commission established December 1, 2004 as the effective date for Section 214, so this has no effect during our main intervention period.

5.2 Data Description

The Home Mortgage Disclosure Act (HMDA) requires financial institutions (including banks, savings associations, credit unions, and other mortgage lending institutions) to annually report disclosures of their lending activities. Using the data submitted by these financial institutions, the Federal Financial Institutions Examination Council releases aggregate lending information on the disposition of mortgage applications by categories (e.g., loans on 1-to-4 family dwellings) at the Census tract level.[22] Census tracts are small, relatively permanent statistical subdivisions of a county, usually consisting of 2,500 to 8,000 persons. When first delineated by the government, they were designed to be homogeneous with respect to population characteristics, economic status, and living conditions.

For each year, we observe the disposition of loan applications by property location and the type of loan. That is, for each Census tract, the data show how many (1-to-4 family home) loans were originated, how many were approved but not accepted, and how many applications were denied, withdrawn, or closed for incompleteness. The data also show the aggregate dollar amounts in each of these five categories. Importantly, the HMDA aggregate reports do not include any resale loans (i.e., loans purchased by institutions, which has action-type code 6) as well as any preapproval denied or approved (loans which have action-type codes 7 and 8, respectively, in an institution's reporting). Thus, our data is based on snapshots at the time of origination or denial which is consistent with our model.

We focus on conventional home-purchase loans and refinancing loans for 1-to-4 family dwellings. These two categories contain by far the largest entries and the available observations in other categories (e.g., FHA, FSA/RHS, and VA loans; home improvement loans) are relatively sparse. In fact, approval standard for government-insured loans may be different from those for conventional or refinancing loans and home-improvement loans may not require a lien or substitute for existing mortgages. To match these properties in our loan-level

[22] The Census tract-level data is publicly available at `http://www.ffiec.gov/hmda`. Loan-level HMDA raw data can be ordered at a cost.

analysis, we exclude from our sample FHA, FSA/RHS, and VA loan types, loan purchased by institution and preapproval action types, not owner-occupied and not applicable occupancy, and home improvement and multi-family loan purposes.

Table 1 shows the variables in our panel data set. In constructing the application denial rates, we divide the number (or dollar amount) of applications that were denied by the sum of the number (or dollar amount) of i) loans originated, ii) loans approved but not accepted, and iii) applications denied.[23] We will refer to the denominator as the number of loan applications. For both home-purchase loans and refinancing loans, mortgage denial rates increased over the sample period. The increase in denial rates in the treatment counties is a little smaller than that in the control counties during the 2001-2004 period and the increase is higher for the treatment counties during the 2003-2006 period. The denial rate is also consistently higher in the treatment counties throughout the sample.

The relatively large upward trend in loan denial rates in both the treatment and control counties over the sample period seems both a national and state-wide phenomenon. Specifically, Figure 2 shows the pre-trends in the denial rates of conventional home purchase loans for the five counties in SFOF MSA, California, and in the US. Noticeably, there is a stark difference between the national and state-level pre-2002 trends in mortgage denial rates, but the pre-2002 trends of the five counties seem consistent with that of the state of California. The upward trend starting from 2002 might be explained by the collapse of the Dot-com bubble, the economic recession, and the September 11, 2001 attacks. Subprime lending also began to grow from 8% or lower to approximately 20% of all mortgages from 2004 to 2006.

To be clear, our results rely on the common trends assumption and we cannot rule out omitted variable biases that might explain the differential trends. For instance, given that San Francisco and Marin counties are relatively more affluent than the other three counties, it is possible that the treatment counties have a higher latent demand for mortgages and

[23]We do not use information on withdrawn or incomplete applications in our calculation because we do not observe the reason for such actions. That is, it may be the lender or the applicant who decided to withdraw an application. Further, withdrawn applicants are likely to apply for a loan elsewhere, and hence by not including them we may avoid double-counting of such applications.

thus experienced larger increases in subprime mortgage lending than the control counties did (Mian and Sufi 2009). Unfortunately, there are no obvious ways to measure the proportion of subprime loans.[24] Further, during the housing boom, many creditworthy borrowers were parties to subprime loans due to fraudulent behavior of lenders. Thus, it is unclear how the proportion of subprime loans might have affected denial rates across the counties.

For control variables, we include tract-level economic characteristics (median income as % of MSA median; % of population below poverty threshold; an indicator for being inside a central city), population characteristics (% of Minority, or Asian, Black, and Hispanic population), and housing characteristics (median age of housing stock; % of owner-occupied housing units; number-of-households to housing-units). Census variables vary between 2001-02 and 2003-06; Median income and city indicator can additionally vary between 2003 and 2004-06. Notice that all control variables, except the central city dummy, have comparable means. This suggests that the adoption of the local ordinance was mainly influenced by the presence of financial institutions in central cities.

Another data set comes from the Department of Housing and Urban Development (HUD)'s Neighborhood Stabilization Program which was authorized under the Housing and Economic Recovery Act of 2008. This is cross-sectional data from December 2008 at the Census tract level which contains government "estimated percent of mortgages to start foreclosure process or be seriously delinquent in past 2 years."[25] HUD warns that these are "foreclosure start" estimates and hence are assumed to overstate the actual number of homes that would become Real Estate Owned. Specifically, HUD states that fewer than half of loans that start the foreclosure process complete it. Thus, when interpreting our results, we reduce the magnitude of estimates by half.

HUD data also contain factors that are said to be "extremely good predictors of fore-

[24]The number of subprime loans are often proxied by associating loans originated by lenders identified by the US Department of Housing and Urban Development (HUD) as subprime specialists. Such esimates include some prime loans from subprime lenders and also exclude some subprime loans from institutions not included in HUD's subprime specialist list, introducing measurement errors.

[25]The data is publicly available at `http://www.huduser.org/nspgis/nsp_map_by_state.html`.

closure problems." These include whether or not loans are high-cost, high-leverage, or both, how much home values have fallen from the peak in the metropolitan areas, and the unemployment rate in 2008. Specifically, HUD calculated total number of mortgages and percent of high-cost and/or high-leverage mortgages in each Census tract based on 2004-2007 HMDA data and also house value changes between peak values and December 2008 values based on a repeat sales method. Additionally, we calculate the fraction of HMDA loans originated in 2003-04 divided by the HUD estimated number of mortgages in 2008. The summary statistics are provided in Table 2.

6 Empirical Analysis

6.1 Main Results

Table 3 and Table 4 contain estimation results from the following difference-in-differences specification:

$$Denial\ Rate_{it} = \beta Treat_{it} + \gamma X_{it} + Tract_i + Year_t + \varepsilon_{it}.$$

where for each tract i and year t, $Treat_{it}$ is an indicator variable for tracts belonging to the three treatment counties during the intervention period and for all tracts in the five counties during the post-intervention period; and X_{it} is a set of Census tract-level characteristics. Standard errors are clustered at the Census tract-level and given in the parentheses.

In these two tables, we present the results using Weighted Least Squares (WLS) because all of our dependent variables are in ratio form and constructed from different sample sizes. That is, denial rates calculated from a smaller number of applications may be less reliable than those calculated from a larger number of applications. Although our results are robust to the use of Ordinary Least Square (OLS), we prefer the WLS estimates because heteroskedastic error terms may bias the standard errors. We use the number of total applications (for home-purchase loans and refinancing loans, respectively), with which we calculated the denial rates, as weights that are inversely proportional to the variance in our estimation.

Table 3 shows the estimation results for conventional home-purchase loans. Specifically, columns (i)–(iii) show the estimation results for mortgage denial rates in numbers, while columns (iv)–(iv) show them for denial rates in dollar amounts. The treatment effect of the privacy ordinance is statistically significant and negative in all specifications, where the magnitude of the effect on mortgage denial rates, both in number and in amount, seems to be around 1%. Similarly, Table 4 replicates the same models for home refinancing loans. The results here indicate that the treatment effect is about a 0.5% decrease in the denial rates for refinancing loans. Overall, these results seem to support our theoretical predictions.

On the other hand, tracts with larger minority populations have significantly higher loan denial rates, where the significance appears somewhat stronger for Asian and Hispanic populations relative to Black populations. This is consistent with the existing literature on statistical discrimination against some ethnic groups in the capital market (see, e.g., Cavalluzzo et al. 2002; Blanchflower et al. 2003; and Cavalluzzo and Wolken 2005). Our results largely confirm their findings — tracts with larger Asian, Black, or Hispanic populations are associated with a more than 5% increase in loan denial rates. Other control variables do not seem to be consistently and significantly correlated with the outcome variables.

6.2 Robustness

There is a relatively large difference in loan denial rates between the treatment and control counties in the pre-intervention period. Further, we cannot rule out the possibility that there is some omitted variable that drives the change in denial rates between the pre and post periods. Here, we address some of these issues using individual loan-level data. Although it is not panel data, the advantages of loan-level analysis are twofold. One is that we can control for lender dummies which would help rule out the possibility that changes in loan rejection policies across lenders account for our difference-in-differences estimates. Another is that we can classify individual loan applications into conforming and non-conforming loans based on the loan amount which can be used to examine the effects of securitization. That is, many lenders sell their loans to government-sponsored enterprises such as Fannie Mae and Freddie Mac shortly after originating them. This is often done because retaining a mortgage represents a significant risk for the lender. However, these government-sponsored enterprises only accept loans that meet certain standards (i.e., conforming loans). One of the most common types of non-conforming loans is the 'jumbo' loan, a loan for an amount that exceeds the limit set by Fannie Mae and Freddie Mac.[26] Because these enterprises do not typically purchase non-conforming loans, lenders may have to retain a larger proportion of them which would mean that lenders have greater incentives to screen non-conforming loan applications relative to conforming loans. Therefore, one would anticipate stronger robustness results for jumbo loans than for conforming loans.

Table 5 shows OLS estimation results using the following linear probability model:[27]

$$Reject_i = \beta Treat_{st} + \gamma X_i + Year_t + County_s + Lender_j + \varepsilon_{ijst}.$$

where for each loan application i, $Treat_{st}$ is an indicator for treatment status for county s and year t; X_i includes an applicant's race (where the excluded category is white), sex, and mortgage-to-income (MTI) ratio; and we also include a full set of lender dummies (of which there are 1483 in total). Standard errors are clustered by lender.

The first two columns show the estimation results by loan purpose, where the treatment effect is statistically significant for purchase loans but insignificant for refinancing loans. Consistent with the previous findings, other coefficient estimates indicate that minority races are significantly more likely to have their loan applications rejected while male applicants are

[26] Conforming loan size limits are \$275,000 in 2001, \$300,700 in 2002, \$322,700 in 2003, \$333,700 in 2004, \$359,650 in 2005, and \$417,000 in 2006.

[27] Given the large number of indicator variables, logit or probit models either do not converge or are imprecisely estimated when they do. Similarly, the covariance matrix is highly singular if we include a full set of Census tract dummies, instead of county dummies.

significantly less likely to be rejected. Also, as expected, the higher the mortgage-to-income ratio, the more likely an application is rejected. Therefore, using this loan-level specification, the previous subsection's results are supported in the case of purchase loans, but not in the case of refinancing loans.

The next two columns show the estimation results using only conforming-size loans. The change is that treatment effect on purchase loans is now marginally insignificant at the 5% level which suggests that the privacy laws might have had only marginal (little) effect on lenders' incentives to screen purchase and refinancing loans when they were likely to be subsequently purchased by government-sponsored enterprises. On the other hand, the last two columns contain estimation results using only jumbo loans. Here, the treatment effect on both purchase and refinancing loans is statistically significant and negative which indicates that the privacy laws had a relatively larger impact on lenders' incentives to screen jumbo loans, presumably because they had to retain a larger proportion of them.

6.3 Corroborating Evidence

Our theoretical model also implies that if loan denial rates go down, then foreclosure rates should eventually go up as more unqualified individuals are approved. Table 6 presents reduced-form estimates of cross-sectional regressions where the dependent variable is the 2007-08 foreclosure start rate. We show WLS estimates using the HUD estimated number of mortgages as inverse variance weights with standard errors clustered by county. Columns (i)–(iii) show that the coefficient on the indicator for the three treatment counties are significant and positively associated with the estimated foreclosure start rate in 2007-08.

To be clear, we cannot provide direct evidence in support of the notion that the 2003-04 local privacy ordinance is causally associated with this rate differential because the foreclosure data is not decomposable by loan age. However, given that the other predictors such as house price change and tract-level loan characteristics absorb a significant amount of variation in the data, the 1% increase in foreclosure start rate (hence, $< 0.5\%$ in predicted foreclosure rate) is interesting and suggestive of our theoretical argument.

To explore this possibility further, in columns (iv)–(vi) we use the share of 2003-04 HMDA loans in the HUD estimated number of mortgages in 2008 interacted with the indicator for the treatment counties. The idea is that if those tracts with higher shares of 2003-04 loans in the treated counties are disproportionately more likely to have higher foreclosure start rates, then it would be consistent with the model's prediction. Here, we do find that the coefficient on the interaction term is statistically significant and positive.

Although our preferred interpretation of these results is one of qualitative support for our theory, the interactive effect is an increase of 1% ($= .2222 \times .0452$) in foreclosure start rate in the treatment counties evaluated at the simple mean of the 2003-04 share. The implied .5% increase in foreclosure rate (i.e., half of 1%) still seems a little high to be accounted for by the 1% decrease in denial rates during 2003-04. However, the share of 2003-04 loans could be higher if we take into account refinancing loans and the decrease in denial rates could explain some part of the foreclosure rate differential.[28]

7 Conclusion

The economic impact of trade in consumer information depends largely on how this information is used. In this paper, consumer types determine a firm's costs of serving them as customers and information obtained in the screening process is traded to another firm with correlated costs. A firm's ability to sell consumer information leads to lower prices, higher screening intensities, higher rejection rates, and, perhaps more importantly, increased ex-ante social welfare. We believe that this paper provides a framework for studying certain aspects of privacy protection in real-world markets, such as financial markets, where prices to qualified consumers are posted upfront. In particular, our model's welfare implication should be given consideration alongside models of price discrimination.

[28]We did not include HMDA refinancing loans in our 2003-04 share calculation because the HUD estimated number of mortgages (the denominator) seems to only take into account purchase loans. The number of refinancing loans was 373,302 in 2003 and 175,692 in 2004 while it was 87,752 in 2007 and 47,680 in 2008.

We closely scrutinized state and local privacy legislations, seeking ordinances that required financial institutions to obtain explicit opt-in consents prior to sharing or selling consumer information. We found statistically reliable evidence that, in areas affected by opt-in policy legislation, loan application denial rates decreased by about 1% for conventional home loans and about 0.5% for refinancing loans. We also showed some evidence that the decrease in loan approval rates may be driven by non-conforming loans and that it may have contributed to an increase in foreclosure rates in the treatment counties. Empirical support for our theoretical predictions suggests some caution when considering legislative proposals for amending the financial-privacy provisions of the GLBA.

References

[1] Acquisti, A., and H. Varian. 2005. Conditioning prices on purchase history. *Marketing Science* 24(3): 367–381.

[2] Armstrong, M. 2006. Recent developments in the economics of price discrimination. Newey, Blundell, Persson, eds., *Advances in Economics and Econometrics: Theory and Applications*. Cambridge University Press.

[3] Blanchflower, D., P. Levine, and D. Zimmerman. 2003. Discrimination in the small-business credit market. *Review of Economics and Statistics* 85(4): 930–943.

[4] Burke, J., C. Taylor, and L. Wagman. 2012. Information acquisition in competitive markets: An application to the US mortgage market. *American Economic Journal: Microeconomics* 4(4): 65–106.

[5] Calzolari, G., and A. Pavan. 2006. On the optimality of privacy in sequential contracting. *Journal of Economic Theory* 130(1): 168–204.

[6] Cavalluzzo, K., L. Cavalluzzo, and J. Wolken. 2002. Competition, small business financing, and discrimination: Evidence from a new survey. *Journal of Business* 75(4): 641–679.

[7] Cavalluzzo, K., and J. Wolken. 2005. Small business loan turndowns, personal wealth, and discrimination. *Journal of Business* 78(6): 2153–2178.

[8] Chen, Y. and Z. Zhang. 2009. Dynamic targeted pricing with strategic consumers. *International Journal of Industrial Organization* 27(1): 43–50.

[9] Conitzer, V., C. Taylor, and L. Wagman. 2012. Hide and seek: Costly consumer privacy in a market with repeat purchases. *Marketing Science* 31(2): 277–292.

[10] Daughety, A., and J. Reinganum. 2010. Public goods, social pressure, and the choice between privacy and publicity. *American Economic Journal: Microeconomics* 2(2): 191–221.

[11] Djankov, S., C. McLiesh, and A. Shleifer. 2007. Private credit in 129 countries. *Journal of Financial Economics* 84(2): 299–329.

[12] Doblas-Madrid, A., and R. Minetti. 2013. Sharing information in the credit market: Contract-level evidence from U.S. firms. *Journal of Financial Economics* 109(1): 198–223.

[13] Fudenberg, D., and J. Villas-Boas. 2006. Behavior-based price discrimination and customer recognition. T. Hendershott, ed., *Handbook on Economics and Information Systems*. North-Holland.

[14] Goldfarb, A., and C. Tucker. 2011. Privacy regulation and online advertising. *Management Science* 57(1): 57–71.

[15] Hermalin, B., and M. Katz. 2006. Privacy, property rights and efficiency: The economics of privacy as secrecy. *Quantitative Marketing and Economics* 4(3): 209–239.

[16] Hertzberg, A., J. Liberti, and D. Paravisini. 2011. Public information and coordination: Evidence from a credit registry expansion. *Journal of Finance* 66(2): 379–412.

[17] Hoel, M., and T. Iversen. 2002. Genetic testing when there is a mix of compulsory and voluntary health insurance. *Journal of Health Economics* 21(2): 253–270.

[18] Hui, K.-L., and I. Png. 2006. Economics of privacy. T. Hendershott, ed., *Handbooks in Information Systems*, Vol. 1. Elsevier.

[19] Johnson, E., and D. Goldstein. 2004. Defaults and donation decisions. *Transplantation*, 78(12): 1713–1716.

[20] Mian, A., and A. Sufi. 2009. The consequences of mortgage credit expansion: Evidence from the U.S. mortgage default crisis. *Quarterly Journal of Economics* 124(4): 1449–1496.

[21] Miller, A., and C. Tucker. 2009. Privacy protection and technology diffusion: The case of electronic medical records. *Management Science* 55(7): 1077–1093.

[22] ———, and ———. 2011. Can health care information technology save babies? *Journal of Political Economy* 119(2): 289–324.

[23] Pagano, M., and T. Jappelli. 1993. Information sharing in credit markets. *Journal of Finance* 48(5): 1693–1718.

[24] ———, and ———. 2002. Information sharing, lending and defaults: Cross-country evidence. *Journal of Banking and Finance* 26(10): 2017–2045.

[25] Posner, R. 1981. The economics of privacy. *American Economic Review* 71(2): 405–409.

[26] Qian, J., and P. Strahan. 2007. How laws and institutions shape financial contracts: The case of bank loans. *Journal of Finance* 62(6): 2803–2834.

[27] Stigler, G. 1980. An introduction to privacy in economics and politics. *Journal of Legal Studies* 9(4): 623–644.

[28] Taylor, C. 2004. Consumer privacy and the market for customer information. *RAND Journal of Economics* 35(4): 631–650.

[29] Taylor, C., and L. Wagman. 2014. Consumer privacy in oligopolistic markets: Winners, losers, and welfare. *International Journal of Industrial Organization* 34(1): 80–84.

[30] Villas-Boas, J. 2004. Price cycles in markets with customer recognition. *RAND Journal of Economics* 35(3): 486–501.

Appendix

Proof of Lemma 1. Whether or not trade is permitted, a consumer's expected utility from applying to purchase the good at a price p_A is

$$U(p_A, n) = (\lambda(1-\alpha)^n + (1-\lambda))(v_A - p_A).$$

Without information trade, firm A's expected profit from each of its applicants is given by

$$\Pi^{NT}(p_A, n) = (\lambda(1-\alpha)^n + (1-\lambda))p_A - (1-\lambda)c_L^A - \lambda(1-\alpha)^n c_H^A - kn.$$

The first-order condition with respect to n (given p_A) is

$$\frac{\partial \Pi^{NT}}{\partial n} = \lambda \ln(1-\alpha)(p_A - c_H^A)(1-\alpha)^n - k \leq 0.$$

Since $\frac{\partial^2 \Pi^{NT}}{\partial n^2} = \lambda(\ln(1-\alpha))^2(p_A - c_H^A)(1-\alpha)^n < 0$, an interior solution obtains if $\frac{\partial \Pi^{NT}}{\partial n} > 0$ at $n = 0$, or $m < \lambda(c_H^A - v_A)$.

Thus, the expected utility assuming interior solutions can be rewritten as

$$U^{NT}(p_A, n) = [\frac{m}{c_H^A - p_A} + (1-\lambda)](v_A - p_A).$$

Differentiating with respect to p_A yields

$$\frac{dU^{NT}}{dp_A} = \frac{m(v_A - c_H^A)}{(c_H^A - p_A)^2} - (1-\lambda) < 0.$$

Similarly, in the case with trade, firm A's profit per application is given by

$$\Pi^T = (\lambda(1-\alpha)^n + (1-\lambda))p_A - (1-\lambda)c_L^A - \lambda(1-\alpha)^n c_H^A - kn +$$
$$(1-\lambda)\lambda(1-(1-\alpha)^n)(c_H^B - c_L^B).$$

The first-order condition with respect to n (given p_A) is

$$\frac{\partial \Pi^T}{\partial n} = \lambda \ln(1-\alpha)(1-\alpha)^n[p_A - c_H^A - (1-\lambda)(c_H^B - c_L^B)] - k \leq 0.$$

Since $\frac{\partial^2 \Pi^T}{\partial n^2} = \lambda[\ln(1-\alpha)]^2(1-\alpha)^n[p_A - c_H^A - (1-\lambda)(c_H^B - c_L^B)] < 0$, an interior solution obtains if $\frac{\partial \Pi^T}{\partial n} > 0$ at $n = 0$, or $m < \lambda[c_H^A - v_A + (1-\lambda)(c_H^B - c_L^B)]$.

Expected utility when information trade is permitted is thus given by

$$U^T(p_A, n) = [\frac{m}{c_H^A - p_A + (1-\lambda)(c_H^B - c_L^B)} + (1-\lambda)](v_A - p_A).$$

Differentiating with respect p_A yields

$$\frac{dU^T(p_A, n)}{dp_A} = \frac{m[v_A - c_H^A - (1-\lambda)(c_H^A - c_L^A)]}{[c_H^A - p_A + (1-\lambda)(c_H^B - c_L^B)]^2} - (1-\lambda) < 0.$$

Proof of Proposition 1. The proof proceeds in two steps.

Step 1: We first show that for a given p_A, under information trade, more information is collected about consumers and the amount of information collected is decreasing in p_A.

Without information trade, given a price p_A, firm A's optimal search intensity $n^*_{NT}(p_A)$ is given by

$$n^*_{NT}(p_A) = \frac{\ln m - \ln \lambda - \ln(c_H^A - p_A)}{\ln(1-\alpha)}.$$

With trade, given a price p_A, its optimal search intensity $n_T^*(p_A)$ is

$$n_T^*(p_A) = \frac{\ln m - \ln \lambda - \ln[c_H^A - p_A + (1-\lambda)(c_H^B - c_L^B)]}{\ln(1-\alpha)}.$$

We need only compare the last term in the numerators. Since $\ln(c_H^A - p_A) < \ln[c_H^A - p_A + (1-\lambda)(c_H^B - c_L^B)]$ and the denominator $\ln(1-\alpha)$ is negative for $\alpha \in (0,1)$, we have $\frac{-\ln(c_H^A - p_A)}{\ln(1-\alpha)} < \frac{-\ln[c_H^A - p_A + (1-\lambda)(c_H^B - c_L^B)]}{\ln(1-\alpha)}$. Hence, it follows that $n_{NT}^*(p_A) < n_T^*(p_A)$. Note that if $p_{A,T} < p_{A,NT}$, then the gap between $c_H^A - p_{A,NT}$ and $c_H^A - p_{A,T} + (1-\lambda)(c_H^B - c_L^B)$ expands.

From the first-order condition of the firm's expected profit without trade,

$$\lambda(1-\alpha)^{n_{NT}(p_{A,NT})}(c_H^A - p_{A,NT}) = m,$$

it follows that $n_{NT}^*(p_{A,NT})$ is decreasing in $p_{A,NT}$.

Similarly, from the first-order condition of the firm's expected profit with trade,

$$\lambda(1-\alpha)^{n_T(p_{A,T})}[c_H^A - p_{A,T} + (1-\lambda)(c_H^B - c_L^B)] = m,$$

it follows that $n_T^*(p_{A,T})$ is decreasing in $p_{A,T}$.

Step 2: Next, we show that under information trade, consumers purchase from firms of type A at a lower price.

Since firms are competing in price, equilibrium profits will be driven down to zero. Therefore, $p_{A,NT}^*$ and $p_{A,T}^*$, along with $n_{NT}^* = n_{NT}(p_{A,NT})$ and $n_T^* = n_T(p_{A,T})$, satisfy

$$p_{A,NT}^* = \frac{(1-\lambda)c_L^A + \lambda(1-\alpha)^{n_{NT}^*}c_H^A + kn_{NT}^*}{\lambda(1-\alpha)^{n_{NT}^*} + (1-\lambda)}$$

and

$$p_{A,T}^* = \frac{(1-\lambda)c_L^A + \lambda(1-\alpha)^{n_T^*}c_H^A + kn_T^* - (1-\lambda)\lambda[1-(1-\alpha)^{n_T^*}](c_H^B - c_L^B)}{\lambda(1-\alpha)^{n_T^*} + (1-\lambda)}.$$

Since $\Pi_A^{NT}(p_{A,NT}^*, n_{NT}^*) = 0$, once information trade is permitted, profits are positive at the price and search intensity $(p_{A,NT}^*, n_{NT}^*)$; that is, $\Pi_A^T(p_{A,NT}^*, n_{NT}^*) > 0$. By Lemma 1, consumers apply to the lowest priced firm. It follows that $p_{A,T}^* < p_{A,NT}^*$ must be satisfied in equilibrium. Combined with Step 1, we further have that $n_T^* > n_{NT}^*$ in a symmetric equilibrium.

Proof of Proposition 2. The proof proceeds in two steps.

Step 1: We first show that there exists a lower bound $b(c_L^B, c_H^B)$ on the difference in the equilibrium prices with and without trade, $p_{A,NT}^* - p_{A,T}^*$.

Notice that for a given search intensity n, the gain from information trade is $(1-\lambda)\lambda(1-(1-\alpha)^n)(c_H^B - c_L^B)$. Since firm A's expected profits are zero in equilibrium without trade, the following relationship must hold when information trade is permitted:

$$p_{A,NT}^* - p_{A,T}^* \geq \frac{(1-\lambda)\lambda(1-(1-\alpha)^{n_{NT}^*})(c_H^B - c_L^B)}{\lambda(1-\alpha)^{n_{NT}^*} + 1 - \lambda},$$

else a firm A possesses a profitable deviation by undercutting its competitors and attracting all consumers while benefiting from a positive expected profit.

Step 2: Next, we compare social welfare with and without information trade.

Welfare without trade, W_{NT}, is given by

$$W_{NT} = (\lambda(1-\alpha)^{n_{NT}} + (1-\lambda))v_A - (1-\lambda)c_L^A - \lambda(1-\alpha)^{n_{NT}}c_H^A - kn_{NT}.$$

Welfare with trade, W_T, is given by

$$W_T = (\lambda(1-\alpha)^{n_T}+(1-\lambda))v_A-(1-\lambda)c_L^A-\lambda(1-\alpha)^{n_T}c_H^A-kn_T+(1-\lambda)\lambda(1-(1-\alpha)^{n_T})(c_H^B-c_L^B).$$

From firm A's first-order conditions, we have $\lambda(1-\alpha)^{n_{NT}^*}(c_H^A - p_{A,NT}^*) = m$ and $\lambda(1-\alpha)^{n_T^*}[c_H^A - p_{A,T}^* + (1-\lambda)(c_H^B - c_L^B)] = m$ for each case. Substituting n_{NT}^* and n_T^*, welfare with information trade is greater than without trade when

$$\frac{m(v_A - p_{A,T}^*)}{c_H^A - p_{A,T}^* + (1-\lambda)(c_H^B - c_L^B)} + (1-\lambda)(v_A - p_{A,T}^*) \geq \frac{m(v_A - p_{A,NT}^*)}{c_H^A - p_{A,NT}^*} + (1-\lambda)(v_A - p_{A,NT}^*).$$

Since $m < \lambda(c_H - v_A)$ by assumption (interior solutions), a sufficient condition for the above inequality to hold is

$$\frac{1-\lambda}{\lambda(c_H^A - v_A)}(p_{A,NT}^* - p_{A,T}^*) \geq \frac{v_A - p_{A,NT}^*}{c_H^A - p_{A,NT}^*} - \frac{v_A - p_{A,T}^*}{c_H^A - p_{A,T}^* + (1-\lambda)(c_H^B - c_L^B)}.$$

This inequality can be rewritten as

$$(1-\lambda)\frac{c_H^A - p_{A,NT}^*}{c_H^A - v_A}(p_{A,NT}^* - p_{A,T}^*)(c_H^A - p_{A,T}^* + (1-\lambda)(c_H^B - c_L^B)) + \lambda(p_{A,NT}^* - p_{A,T}^*)(c_H^A - v_A)$$

$$\geq \lambda(v_A - p_{A,NT}^*)(1-\lambda)(c_H^B - c_L^B).$$

Since $p_{A,NT}^* > p_{A,T}^*$ and $0 < c_H - v_A < c_H - p_{A,NT}^*$, whereby $\frac{c_H - P_{A,NT}}{c_H - v_A} > 1$, a sufficient condition for the above is

$$p_{A,NT}^* - p_{A,T}^* \geq \lambda(v_A - p_{A,NT}^*).$$

Using $p_{A,NT}^* - p_{A,T}^* \geq \frac{(1-\lambda)\lambda(1-(1-\alpha)^{n_{NT}^*})(c_H^B - c_L^B)}{\lambda(1-\alpha)^{n_{NT}^*}+1-\lambda}$ from Step 1 and simplifying, a sufficient condition is given by

$$c_H^B - c_L^B \geq \frac{(1-\lambda+\lambda(1-\alpha)^{n_{NT}^*})(v_A - p_{A,NT}^*)}{(1-\lambda)(1-(1-\alpha)^{n_{NT}^*})} \equiv \bar{c}.$$

The right-hand side of the inequality does not depend on $c_H^B - c_L^B$, giving a lower bound $\bar{c}$.

Proof of Proposition 3. The proof proceeds in two steps.

Step 1: We first show that a consumer's expected utility from applying to purchase good A is decreasing in the price P_A. To save notation, we let $v_A = v_{A,L}$.

Whether or not information trade is permitted, a consumer's expected utility from applying to a firm A is now given by

$$U(p_A, n) = (\lambda(1-\alpha)^n + (1-\lambda))(v_A - p_A) - \lambda(1-\alpha)^n(v_A - v_{A,H}),$$

and for a given p_A a firm A chooses $n(p_A)$ from its first-order condition, $\lambda(1-\alpha)^n(c_H^A - p_A) = m$ (without trade) and $\lambda(1-\alpha)^n[c_H^A - p_A + (1-\lambda)(c_H^B - c_L^B)] = m$ (with trade). Thus, a consumer's expected utility is

$$U(p_A, n) = \left(\frac{m}{c_H^A - p_A + \mathbf{1}\{\text{trade}\}(1-\lambda)(c_H^B - c_L^B)} + (1-\lambda)\right)(v_{A,H} - p_A) + (1-\lambda)(v_A - v_{A,H}),$$

where $\mathbf{1}\{\text{trade}\}$ is the indicator function for information trade. Differentiation with respect to p_A yields

$$\frac{dU}{dp_A} = -\frac{m(c_H^A - v_{A,H} + \mathbf{1}\{\text{trade}\}(1-\lambda)(c_H^B - c_L^B))}{(c_H^A - p_A + \mathbf{1}\{\text{trade}\}(1-\lambda)(c_H^B - c_L^B))^2} - (1-\lambda),$$

which is negative since $c_H > v_{A,H}$ and $c_H > p_A$.

Step 2: Next, we show that a symmetric equilibrium consists of an analogous characterization to the base model. Notice that the planner's problem is equivalent to the monopolist's problem.

Without information trade, the highest price that a monopolist can charge has to satisfy consumers' participation constraints, $(1-\lambda)(v_A - p_A) + \lambda(1-\alpha)^n(v_{A,H} - p_A) \geq 0$. In equilibrium,

$$p_A^* = \frac{(1-\lambda)v_A + \lambda(1-\alpha)^n v_{A,H}}{1-\lambda+\lambda(1-\alpha)^n}.$$

The monopolist's profit is given by $(1-\lambda+\lambda(1-\alpha)^n)p_A - (1-\lambda)c_L^A - \lambda(1-\alpha)^n c_H^A - kn$. Substituting for p_A^*, the monopolist's profit can be rewritten as $\lambda(1-\alpha)^n(v_{A,H} - c_H^A) + (1-\lambda)(v_A - c_L^A) - kn$. The first term is negative and represents the cost of selling to high-cost consumers. Differentiating to obtain the first-order condition gives

$$\lambda(1-\alpha)^n(c_H^A - v_{A,H}) = m$$

A simple comparison between the optimal search condition employed by the monopolist above and the optimal search condition employed by a firm A in equilibrium, given by $\lambda(1-\alpha)^n(c_H^A - p_{A,NT}) = m$, reveals that in equilibrium applicants are not sufficiently screened relative to the efficient level since $p_A > v_{A,H}$.

It is straightforward to show that the problem is analogous in the case of information trade. That is, comparing the optimal search condition employed by a monopolist, $\lambda(1-\alpha)^n(c_H^A - v_{A,H} + (1-\lambda)(c_H^B - c_L^B)) = m$, to the optimal search condition employed by a firm A, given by $\lambda(1-\alpha)^n(c_H^A - p_A + (1-\lambda)(c_H^B - c_L^B)) = m$, reveals the following: Since $p_{A,T} < p_{A,NT}$ is satisfied by Proposition 1, allowing for information trade would move the outcome closer to the social optimum.

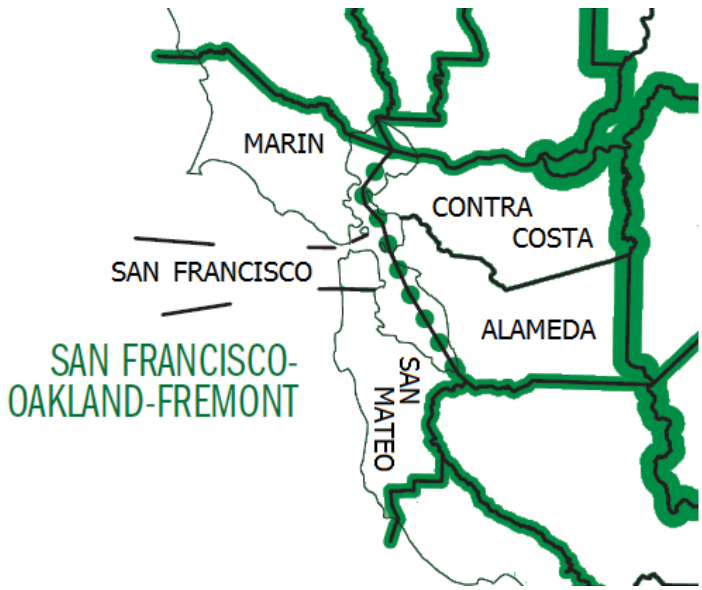

Figure 1: Map of the five counties in the San Francisco-Oakland-Fremont MSA.

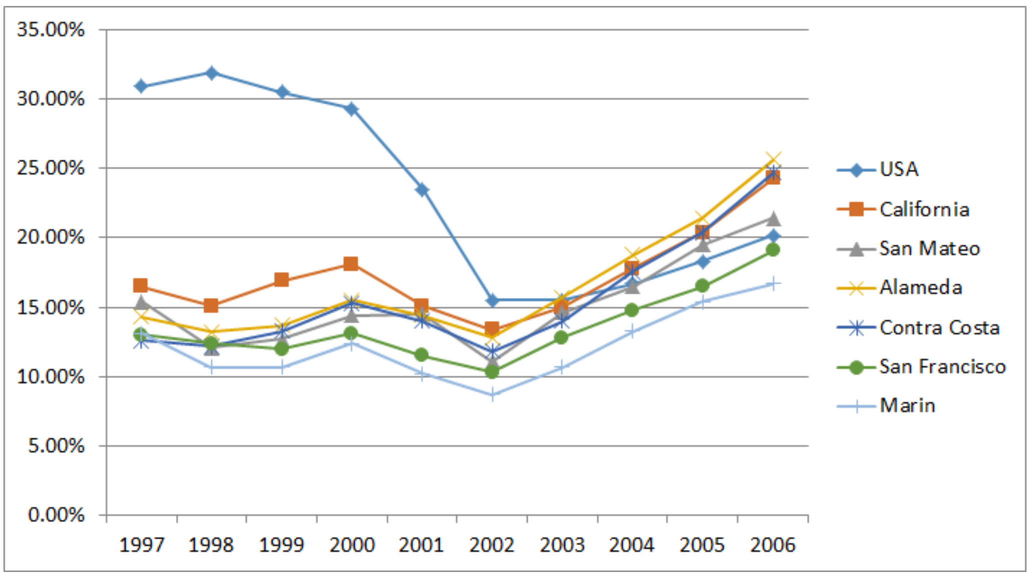

Figure 2: Denial rates of conventional home-purchase loans.

	Treatment Group		Control Group	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Pre-intervention (2001, 2002)				
Purchasing loan denial rate (in number)	.1387	(.0883)	.1077	(.0940)
Purchasing loan denial rate (in $000's)	.1342	(.0891)	.1043	(.1026)
Number of purchasing loans originated	123.6	(143.8)	74.01	(55.26)
Refinancing loan denial rate (in number)	.1478	(.0804)	.1392	(.1104)
Refinancing loan denial rate (in $000's)	.1487	(.0765)	.1405	(.1086)
Number of refinancing loans originated	429.7	(391.7)	272.2	(209.5)
During intervention (2003, 2004)				
Purchasing loan denial rate (in number)	.1649	(.0826)	.1406	(.0945)
Purchasing loan denial rate (in $000's)	.1615	(.0856)	.1354	(.0919)
Number of purchasing loans originated	158.4	(177.3)	86.89	(81.84)
Refinancing loan denial rate (in number)	.1796	(.0929)	.1784	(.1286)
Refinancing loan denial rate (in $000's)	.1914	(.0951)	.1854	(.1253)
Number of refinancing loans originated	478.5	(426.0)	291.6	(244.8)
Post-intervention (2005, 2006)				
Purchasing loan denial rate (in number)	.2173	(.0972)	.1815	(.1258)
Purchasing loan denial rate (in $000's)	.2178	(.1014)	.1782	(.1265)
Number of purchasing loans originated	170.5	(201.3)	87.65	(84.10)
Refinancing loan denial rate (in number)	.2467	(.0946)	.2280	(.1265)
Refinancing loan denial rate (in $000's)	.2604	(.0973)	.2368	(.1266)
Number of refinancing loans originated	275.3	(267.5)	131.5	(97.12)
Control variables (2001-2006)				
Median income, % of MSA median	104.4	(45.36)	98.27	(44.52)
% of population below Poverty Line	9.295	(9.209)	10.80	(8.581)
Inside central city?	.3820	(.4859)	.7922	(.4059)
% of Minority population	47.70	(26.47)	45.18	(26.86)
% of Asian population	.1600	(.1347)	.2297	(.1998)
% of Black population	.1227	(.1851)	.0768	(.1323)
% of Hispanic population	.1643	(.1412)	.1202	(.1304)
Median age of housing stock	35.41	(13.89)	47.29	(13.91)
% of owner-occupied units	.6838	(.2056)	.5162	(.2396)
Ratio of households to housing units	.9674	(.0851)	.9459	(.0681)
Number of observations (tract x year)	3793		1304	

Table 1. Summary Statistics of Panel Data

Treatment group comprises all Census tracts in Alameda, Contra Costa, and San Mateo Counties; Control group comprises all Census tracts in Marin and San Francisco Counties. All data come from Federal Financial Institutions Examination Council.

Variable	Treatment Counties Mean	Treatment Counties Std. Dev.	Control Counties Mean	Control Counties Std. Dev.
Estimated foreclosure start rate	.0985	(.0436)	.0346	(.0237)
Estimated number of mortgages	990.8	(893.9)	601.3	(418.9)
Number of 2003-2004 HMDA loans	227.5	(252.8)	131.6	(116.1)
Share of 2003-2004 HDMA loans	.2222	(.0597)	.2346	(.1552)
House price change from peak value	–.2253	(.0743)	–.0936	(.0000)
Unemployment rate	.0584	(.0062)	.0511	(.0030)
% of low-cost, high-leverage mortgages	.3671	(.0560)	.3716	(.0747)
% of high-cost, low-leverage mortgages	.0307	(.0258)	.0169	(.0145)
% of high-cost, high-leverage mortgages	.0912	(.0677)	.0444	(.0537)
Number of observations (tract)	643		226	

Table 2. Summary Statistics of Cross-Sectional Data

House price change and unemployment rate are at the county level; All other variables are at the Census tract level. All data except HMDA loans are from the Department of Housing and Urban Development's Neighborhood Stabilization Program.

	Denial Rate in Number			Denial Rate in Amount		
Variable	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Treatment	–.0087**	–.0107**	–.0102**	–.0090**	–.0111**	–.0109**
	(.0040)	(.0042)	(.0043)	(.0042)	(.0043)	(.0044)
Median income %		–.0001	–.0002		–.0001	–.0002
		(.0001)	(.0001)		(.0001)	(.0001)
Below poverty %		–.0002	–.0002		.0000	.0001
		(.0005)	(.0005)		(.0006)	(.0006)
Inside city?		–.0017	–.0016		–.0010	–.0006
		(.0033)	(.0033)		(.0035)	(.0035)
Minority %		.0006***			.0006***	
		(.0002)			(.0002)	
Asian %			.0679*			.0652*
			(.0351)			(.0367)
Black %			.0647*			.0566
			(.0383)			(.0376)
Hispanic %			.0537			.0710*
			(.0356)			(.0375)
Median house age			–.0004			–.0002
			(.0004)			(.0005)
Owner-occupied %			–.0007			.0176
			(.0225)			(.0248)
HHD to housing			–.0228			–.0109
			(.0442)			(.0461)
Tract dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	5055	5055	5035	5055	5055	5035
R^2	.7590	.7597	.7607	.7580	.7588	.7596

Table 3. Difference-in-Difference Models (Purchase Loans)

All specifications are Weighted Least Squares where the weight is the number of total purchase loan applications (the denominator). Standard errors are clustered by tract and reported in the parentheses.

Significance level: *** 1%, ** 5%, * 10%.

	Denial Rate in Number			Denial Rate in Amount		
Variable	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Treatment	–.0030	–.0051**	–.0051**	–.0034	–.0059**	–.0062**
	(.0020)	(.0021)	(.0022)	(.0023)	(.0024)	(.0025)
Median income %		–.0001	–.0001		–.0000	–.0000
		(.0000)	(.0001)		(.0001)	(.0001)
Below poverty %		–.0005	–.0006		–.0004	–.0004
		(.0004)	(.0004)		(.0004)	(.0004)
Inside city?		.0047**	.0044**		.0038*	.0036
		(.0020)	(.0020)		(.0023)	(.0023)
Minority %		.0005***			.0006***	
		(.0001)			(.0001)	
Asian %			.0718***			.0813***
			(.0188)			(.0224)
Black %			.0419*			.0441*
			(.0221)			(.0239)
Hispanic %			.0556***			.0897***
			(.0196)			(.0210)
Median house age			–.0001			–.0002
			(.0002)			(.0003)
Owner-occupied %			–.0072			–.0079
			(.0197)			(.0216)
HHD to housing			–.0203			–.0113
			(.0309)			(.0341)
Tract dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	5084	5084	5054	5083	5083	5053
R^2	.9117	.9126	.9130	.8919	.8928	.8933

Table 4. Difference-in-Difference Models (Refinancing Loans)
All specifications are Weighted Least Squares where the weight is the number of total refinancing loan applications (the denominator). Standard errors are clustered by tract and reported in the parentheses.
Significance level: *** 1%, ** 5%, * 10%.

	Whole Sample		Conforming Loans		Jumbo Loans	
Variable	Purch.	Refi.	Purch.	Refi.	Purch.	Refi.
Treatment	–.0146***	–.0028	–.0141*	.0026	–.0153***	–.0098***
	(.0050)	(.0023)	(.0074)	(.0022)	(.0040)	(.0036)
Appl. Native	.0392***	.0677***	.0376***	.0685***	.0381***	.0703***
	(.0097)	(.0082)	(.0108)	(.0085)	(.0086)	(.0083)
Appl. Asian	.0277***	.0205***	.0259***	.0215***	.0273***	.0216***
	(.0029)	(.0035)	(.0037)	(.0033)	(.0035)	(.0040)
Appl. African	.0705***	.0677***	.0803***	.0681***	.0548***	.0753***
	(.0058)	(.0058)	(.0061)	(.0064)	(.0087)	(.0071)
Appl. Pacific	.0362***	.0523***	.0325***	.0544***	.0402***	.0616***
	(.0089)	(.0093)	(.0097)	(.0097)	(.0080)	(.0084)
Appl. male	–.0055***	–.0109***	.0002	–.0092***	–.0098***	–.0189***
	(.0016)	(.0024)	(.0020)	(.0025)	(.0017)	(.0020)
MTI	.0016***	.0025***	.0014	.0033***	.0018***	.0020***
	(.0006)	(.0008)	(.0012)	(.0013)	(.0007)	(.0006)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
County dummies	Yes	Yes	Yes	Yes	Yes	Yes
Institution dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	529913	1267089	260011	718485	269902	548604
R^2	.1188	.1923	.1155	.2025	.1261	.1914

Table 5. Linear Probability Models (Loan Rejections)
All specifications are Ordinary Least Squares with a full set of dummy variables. Standard errors are clustered by institution and reported in the parentheses.
Significance level: *** 1%, ** 5%, * 10%.

	Estimated Foreclosure Start Rate					
Variable	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Treatment counties	.0708**	.0130***	.0116**			
	(.0158)	(.0010)	(.0029)			
Treat x 0304 share				.2996***	.0547***	.0452***
				(.0581)	(.0033)	(.0080)
2003-04 share				–.0780	–.0158	–.0359
				(.1055)	(.0080)	(.0172)
House price change		–.2453***	–.1097		–.2534***	–.1229*
		(.0345)	(.0519)		(.0372)	(.0472)
Unemployment rate		–.1784*	1.410*		–.2789	1.292
		(.0761)	(.6153)		(.1447)	(.6157)
Low-cost high-lev %		–.1509***	–.1708***		–.1522***	–.1715***
		(.0110)	(.0134)		(.0096)	(.0121)
high-cost low-lev %		.2515***	.2560***		.2192***	.2514***
		(.0366)	(.0251)		(.0395)	(.0226)
high-cost high-lev %		.3863***	.3857***		.3897***	.3826***
		(.0348)	(.0128)		(.0331)	(.0132)
Median income %			–.0000**			–.0000
			(.0000)			(.0000)
Below poverty %			–.0002			–.0002
			(.0003)			(.0002)
Inside city?			–.0084**			–.0084**
			(.0022)			(.0022)
Asian %			–.0029			–.0026
			(.0106)			(.0108)
Black %			–.0073			–.0059
			(.0044)			(.0043)
Hispanic %			.0122			.0144
			(.0185)			(.0179)
Median house age			–.0002***			–.0002***
			(.0000)			(.0000)
Owner-occupied %			.0028			.0015
			(.0046)			(.0040)
HHD to housing			.0136			.0188
			(.0110)			(.0115)
N	868	868	865	868	868	865
R^2	.3269	.9561	.9715	.3602	.9568	.9710

Table 6. Reduced-Form Models (Foreclosure Starts)
All specifications are Weighted Least Squares where the weight is the HUD estimated number of mortgages. Standard errors are clustered by county and reported in the parentheses.
Significance level: *** 1%, ** 5%, * 10%.