Public Disclosure and Consumer Financial Protection

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The U.S. Consumer Financial Protection Bureau has released a database of consumer complaints about banks' financial products to the public since 2013. We find a greater reduction in mortgage applications to banks that receive more mortgage complaints in local markets after the disclosure. The effect is stronger in areas with more sophisticated consumers and higher credit competition, and for banks receiving more severe complaints. The number of monthly mortgage complaints per bank exhibits faster mean reversion after the publication of the database. These findings suggest that the public disclosure of mortgage complaints enhances product market discipline and consumer financial protection.

Keywords: Public Disclosure, Mortgages, Complaints, Applications

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1. Introduction

Consumers in financial markets often lack information about the quality of financial products (Campbell et al., 2011; Ryan et al., 2011). It is difficult for consumers to learn from experience since they undertake major financial decisions (e.g., select a mortgage) infrequently. Outcomes of these decisions occur over time, perhaps decades, and are subject to ex-post noise, such as changes in macroeconomic and borrower circumstances. Moreover, social taboos regarding discussing personal finances often hinder the diffusion of experience, and self-serving financial advisors may distort their recommendations. Even when presented with relevant information, consumers may not understand it due to processing biases, inattention, and financial illiteracy. Mounting evidence indicates that financial institutions take advantage of consumers.[1]

The recent financial crisis triggered a surge of interest in regulating consumer financial markets (Financial Crisis Inquiry Commission, 2011; Kirsch and Squires, 2017). The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 created the Consumer Financial Protection Bureau (CFPB) to safeguard consumer interests. Since 2011, the CFPB has accepted complaints about the financial products and services provided by the depository institutions under its jurisdiction (i.e., total assets greater than $10 billion, hereafter "banks"). Since 2013, the CFPB has released a complaint database to the public. The data include individual complaints, their submission dates, complainants' 5-digit ZIP Codes, types of products and issues (without narratives), and the names and responses of the banks involved. The purpose of this public disclosure is to "empower consumers to better understand and detect instances of unfair or deceptive practices, and … alleviate problems upfront by helping consumers avoid bad actors" (CFPB, 2013). By doing so, the bureau "intends for its complaint data disclosures to improve the transparency and efficiency of such consumer financial markets" (CFPB, 2013). Despite the

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[1] For studies of limited learning from experience or other consumers, see Zelizer (1997) and Hong et al. (2004). For studies of distorted recommendations from financial advisors, see Inderst and Ottaviani (2012), Guiso et al. (2018), and Egan et al. (2019). For studies of consumer biases, inattention, and financial illiteracy, see Guiso et al. (2008), Keys et al. (2016), DellaVigna (2009), Ponce et al. (2017), Gabaix (2019), Lusardi et al. (2010), and Lusardi and Tufano (2015). For studies of financial exploitation of consumers, see Gabaix and Laibson (2006), Agarwal et al. (2015), and Gurun et al. (2016) and literature reviews by Campbell (2006, 2016).

importance of the stated goals, little evidence exists on the effectiveness of this disclosure in protecting consumers.

In this paper, we provide such evidence by examining mortgage complaints for several reasons. First, mortgages are the single largest financial transaction for most households, involving millions of homeowners and trillions of dollars (Tufano, 2009; Ryan et al., 2011).[2] Second, 55% of the complaints in the database as of the release date are mortgage-related. Third, the availability of loan-level mortgage application information from the Home Mortgage Disclosure Act (HMDA) database enables us to make direct inferences about consumer choice. To address our line of inquiry, we ask the following questions. Does the disclosure of more mortgage complaints against a bank lead to fewer mortgage applications to the bank? Moreover, does such public disclosure incentivize the bank to act to reduce mortgage complaints?

It is a priori unclear whether the release of mortgage complaints influences the decisions of consumers and banks. Critics of the disclosure cast doubt on the usefulness of the database. Several trade associations express concerns that the accusations in the complaints are “unverified, unrepresentative, lacking in context, and open to manipulation” (CFPB, 2012). Specifically, the CFPB does not verify the content of the complaints in its database and acknowledges that these complaints represent the experience of a non-random subset of consumers who have chosen to appeal to the bureau. For the protection of consumers’ privacy, the disclosures exclude narrative fields that expressly call for personally identifying information, leaving little context for users to understand the nature of the complaints. Another impediment to the effectiveness of this disclosure policy is that consumers, especially unsophisticated ones, may not be aware of or have the capacity to process the data (Woodward and Hall, 2012; Allen et al., 2013). For example, meaningful use of the disclosures requires appropriate normalization for the scale of a bank’s operation in each local market (CFPB, 2013), which is beyond the capability of many consumers. Even if consumers

[2] Campbell (2016) reports that mortgage debt in the United States accounts for 52.7% of household debt, followed by vehicle, student, and other types of loans (31.2%) and credit card debt (12.1%). According to the American Community Survey and the U.S. Flow of Funds, by the end of 2016, 48 million homeowners had a mortgage, and the total mortgage debt amounted to $9.7 trillion.

fully understand the disclosures, they have few alternatives if the local residential mortgage-origination market is concentrated (Stanton et al., 2014). To the extent that disclosing mortgage complaints reveals little useful information and thus does not elicit consumers' responses, banks will not have incentives to reduce consumer dissatisfaction (Fung et al., 2004).

On the other hand, there are several reasons why public disclosure of mortgage complaint information can protect consumers. First, the CFPB has taken measures to enhance the informativeness of the disclosures. If banks "are unable to verify the commercial relationship with the consumer who filed the complaint or believe the complaint was from an unauthorized third party…the bureau will withhold such complaints from publication" (CFPB, 2013). Additionally, "the bureau takes steps to consolidate duplicate complaints from the same consumer into a single complaint" (CFPB, 2013). Second, the public database essentially creates an online word-of-mouth platform, which is more powerful than traditional social learning in aggregating and disseminating the wisdom of crowds (Chevalier and Mayzlin, 2006; Kremer et al., 2014; Che and Horner, 2018; Bergemann and Bonatti, 2019). Third, consumers do not necessarily have to use the database directly. Consumer organizations, researchers, and other third parties can mine the database and help consumers make more informed decisions (CFPB, 2012). To the extent that these reasons dominate, after the disclosure, we expect a greater reduction in mortgage applications to banks that receive more mortgage complaints. The reduction, along with other reputational costs, should incentivize banks to take action to reduce mortgage complaints.

We examine CFPB-supervised banks (those covered in the complaint data) with mortgage applications in the HMDA database. We obtain the mortgage complaints against these banks from the CFPB consumer complaint database. This database was released on March 28, 2013, covering complaints dating from December 1, 2011. We begin by examining the premise that the disclosure of these complaints reveals new information regarding the quality of banks' mortgage products and services. We find that the intensity of mortgage complaints as of the disclosure date is positively associated with the frequency of CFPB enforcement actions and the settlement amounts from these actions over the next five years and is negatively associated with customer satisfaction scores from *Consumer Reports*. We also show that the banks' stock prices on average react significantly negatively to the disclosure event. The magnitude of the negative reaction increases with the intensity of mortgage complaints released on the event day. This initial reaction does not reverse over the next six months. The results suggest that the disclosure of consumer complaints provides new information to the public, with more intense complaints indicating that the associated banks have poorer quality mortgage products and services, and thus will likely generate lower future cash flows.

For the primary analysis, we construct a sample at the bank-county-year level during 2011-2015.[3] The dependent variable captures the annual county-level volume of mortgage applications for each bank. The test variable is an interaction between a bank's county-level exposure to mortgage complaints and an indicator equal to one for the years during and after the public disclosure (i.e., 2013-2015), and zero otherwise (*Post*). We measure the exposure using the number of mortgage complaints as of the disclosure date from a given county against the bank, scaled by the number of mortgage originations by the bank in that county during 2011 (i.e., the first year of our sample period). The final sample consists of 39,263 bank-county-years, representing 118 unique banks and 29,151,375 mortgage applications.

The main multivariate tests are regressions of the annual county-level volume of mortgage applications to a bank on its county-level exposure to mortgage complaints interacted with *Post*, an array of control variables at the bank-county-year level, and county-year, bank-year, and bank-county fixed effects. This specification allows us to isolate the effects of public disclosure from those of many oft-cited confounding factors. In particular, the county-year fixed effects capture economic shocks to local credit demand (e.g., business cycles, industry composition, and housing prices). The bank-year fixed effects absorb bank-specific shocks (e.g., changes in regulatory capital ratios, risk management, and bank liquidity; Gilje et al. 2016) that may be correlated with both mortgage complaints and applications. The bank-county fixed effects remove time-invariant

[3] For each bank, we aggregate applications and conduct analyses at the county level as the mortgage literature treats a county as a local market (Newman and Wyly, 2004; Pence, 2006; Gilje et al., 2016; Cortes and Strahan, 2017; Mian and Sufi, 2017). Aggregating applications at the ZIP, the Metropolitan Statistical Area (MSA), and the state levels does not alter our inferences, as shown in Table A1 of the Internet Appendix. We also find robust results using bank-level complaints in an alternative specification and discuss weaknesses of that approach in Section 4.2.

bank-county heterogeneity, such as the distance from a county to a bank's headquarters or to a regulator's field offices. As discussed in detail in Section 3, this research design permits a comparison of changes in mortgage applications around the disclosure year for banks with different levels of complaints in a county relative to counties in which they receive the same level of complaints. This design essentially resembles a generalized difference-in-differences-in-differences approach (Gruber, 1994; Pischke, 2005; Imbens and Wooldridge, 2007). Throughout our analyses, we also control for the presence and size of the bank's branches and its mortgage approval rates in a county in the previous year.

We find that, after the publication of the database, banks with more mortgage complaints in a county experience a greater reduction in both the number and the dollar amount of mortgage applications from that county. A one standard deviation increase in disclosed mortgage complaints is associated with a 10.5% decrease in the number and a 9.1% decrease in the dollar amount of mortgage applications. The decrease does not occur one year before or during the release year, and first appears one year after the release (i.e., in 2014). The result suggests that consumers did not have sufficient knowledge about banks' mortgage quality through social learning prior to the disclosure. To assess the robustness of our results, we perform sensitivity tests using alternative samples, alternative variables to scale the number of mortgage complaints, and alternative loan application measures. Our inferences remain unchanged. Taken together, the results suggest that making mortgage complaint information publicly available helps consumers avoid lenders with low-quality products and services.

We conduct three additional sets of tests. First, despite the triple-differences design, confounding events at the bank-county-year level (such as a local recession that particularly affects banks with more complaints) may still exist. We conduct a placebo test by relating changes in local small business lending around the disclosure to mortgage complaints. We do not find a significant association between these two variables. Another confounding event is that independent of the disclosure, local community groups may have waged campaigns in 2013 against banks with bad reputations, which likely received more consumer complaints (about not only mortgages but other financial products) in local areas. These campaigns can provoke customer boycotts, resulting in fewer mortgage applications from those areas to the target banks (Squires, 2003; Dou and Zou, 2019). We find that non-mortgage complaints (e.g., complaints about credit cards or bank accounts) also disclosed by the CFPB cannot explain the changes in local mortgage applications around the disclosure. Second, although we include bank-year fixed effects in the model to account for bank characteristics, banks with diverse characteristics may respond differently to local shocks other than the disclosure of complaints. To mitigate this concern, we show that the results are resilient to using a sample of matched banks, in which banks exhibit indistinguishable size, equity, return on assets, and deposits. Third, we test a number of cross-sectional predictions on factors that are likely to strengthen consumers' responses to complaint disclosures. We predict and find that the disclosure effect is more pronounced for counties with more sophisticated consumers (i.e., more high school graduates) and higher credit competition, as well as for banks with more severe complaints. We also find a stronger disclosure effect in states with greater changes in Internet searches for the keyword "CFPB" around the disclosure and in states with more consumer groups that file comment letters in favor of the public disclosure of consumer complaints. The results suggest that Internet searches and consumer groups play a role in disseminating the complaint information.

Buchak et al. (2018) observe a decline in traditional banks' market share in residential mortgage origination during 2007-2015, particularly in counties with more regulatory burden on traditional banks, more minorities, and worse socioeconomic conditions (e.g., fewer high school graduates). This trend is unlikely to explain our findings for several reasons. First, we examine the variation in customer reactions (i.e., mortgage applications) within large traditional banks (i.e., CFPB-supervised banks) as opposed to mortgage originations across traditional and shadow banks. Second, we have controlled for the presence and size of banks' branches as well as their mortgage approval rates in a county in the previous year to account for the scale of their local mortgage operations. Third, our findings are concentrated in counties with more high school graduates, where the trend observed by Buchak et al. (2018) is less prevalent.

Finally, we explore the disciplinary effect of the disclosure on banks. Because the number of complaints tends to mean revert, we examine the speed of mean reversion in the number of monthly mortgage complaints before and after the public disclosure. We find that banks exhibit faster mean reversion in the number of monthly mortgage complaints after the disclosure; the result is driven by banks with a high number of mortgage complaints. For these bad performers, the increase in mean reversion is concentrated among counties with more sophisticated consumers and higher credit competition as well as among banks with more severe complaints. Together, the results suggest that the disclosure of mortgage complaints disciplines banks to improve the consumer experience with their mortgage products and services.

This study contributes to the debate about the costs and benefits of consumer financial protection measures implemented after the recent financial crisis (e.g., Agarwal et al., 2015; Egan et al., 2019), in particular regarding the efficacy of the CFPB's complaint disclosure policy. Consumer groups advocated this policy, while financial institutions strongly opposed it (CFPB, 2013). Members of Congress and the bureau's acting director have proposed making the complaint database invisible to the public.[4] Our findings suggest that public disclosure of complaints facilitates consumer protection in mortgage markets, and eliminating this disclosure may reduce mortgage consumers' welfare.

We contribute to the literature on the disciplinary effect of disclosure. While many studies focus on the discipline imposed by capital providers (Flannery and Sorescu, 1996; Gelos and Wei, 2005; Jin and Myers, 2006; Doidge et al., 2007; Hope and Thomas, 2008; Hermalin and Weisbach, 2012; Lo, 2015; Dou et al., 2019), we examine product market discipline and document adverse consequences to banks of disclosure of their provision of inferior products and services in consumer financial markets. Our paper also adds to the literature on the effectiveness of regulation through disclosure and transparency (Fung et al., 2004; Leuz and Wysocki, 2016). Although disclosure policies are increasingly used as a public policy instrument to encourage or discourage

[4] See "Public window on financial complaints could be closing soon," July 10, 2017, AP News; "CFPB could hide consumer complaints from public, advocates fear," April 14, 2018, MarketWatch; and "Consumer bureau looks to end public view of complaints database," April 25, 2018, The New York Times. At an event in April, the bureau's acting director, Mick Mulvaney, said, "I don't see anything in here [the Dodd-Frank Act] that I have to run a Yelp for financial services sponsored by the federal government…I don't see anything in here [the Dodd-Frank Act] that says that I have to make all of those public."

certain behaviors and business practices, little is known about where and when such policies advance regulatory goals (Jin and Leslie, 2003; Fung et al., 2004; Winston, 2008; Dranove and Jin, 2010; Ben-Shahar and Schneider, 2014; Christensen et al., 2018; Duguay et al., 2019; Rauter, 2020).[5] Our findings suggest that disclosure of complaint data facilitates consumer financial protection, particularly when consumers are more sophisticated, when credit markets are more competitive, and when disclosed complaints are more severe.

2. Background, Related Research, and Hypothesis Development

2.1 Background

The Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 created the CFPB to protect consumers of financial products and services, and to encourage the fair and competitive operation of consumer financial markets. The CFPB initially accepted consumer complaints about credit cards starting in July 2011 and later expanded to accept complaints about mortgages, bank accounts, credit reporting, and other financial products and services. Consumers can submit complaints through the bureau's website and in various other ways. After confirming the commercial relationship between a consumer and a bank, the CFPB sends the consumer's complaint to the bank for a response within 15 calendar days.[6] By collecting complaint data, the bureau can identify trends and problems in the marketplace so that it can set supervision, enforcement, and market monitoring priorities.

On June 19, 2012, the CFPB launched a beta version of the Consumer Complaint Database that published individual credit card complaints dating back to June 1, 2012. On October 10, 2012, the bureau added credit card complaints back to December 1, 2011. On March 28, 2013, the database was expanded to disclose complaints about mortgages, bank accounts or services,

[5] Prior research shows that regulatory disclosure policies are effective in some settings, such as restaurant hygiene quality cards (Jin and Leslie, 2003), but not in others, such as patient safety disclosure (Mukamel and Mushlin, 2001). See Ben-Shahar and Schneider (2014) for "a survey of the empirical literature documenting the failure of the mandated disclosure regime in informing people and in improving their decisions."

[6] If a complaint cannot be closed within 15 calendar days, a bank may indicate that its work on the complaint is "in progress" and provide a final response within 60 calendar days. A response will be considered untimely outside of the 60-day window. As of the disclosure date (i.e., March 28, 2013), 96.8% of complaints receive a timely response.

consumer loans, and student loans. Mainstream media immediately reported the availability of this database to the public.[7] Mortgage complaints date back to December 1, 2011, whereas complaints about the other three financial products date back to March 1, 2012. Since the initial release, new complaints have been posted daily to the public database. As of the disclosure date of March 28, 2013, the database includes 81,680 individual complaints. The majority are mortgage complaints (54.9% = 44,857/81,680), followed by credit card complaints (22.8% = 18,659/81,680) and next by bank account or service complaints (18% = 14,705/81,680). Table A2 of the Internet Appendix shows the breakdown of complaints by the type of financial product and the breakdown by issue for mortgage and credit card complaints.

The database contains the following information for each complaint: the type of financial product, the consumer's ZIP Code, the date of submission, and the name of the bank involved. The database also includes information about the bank's response, such as whether the response was timely, whether the bank provided (monetary or non-monetary) relief or just an explanation, and whether the consumer disputed the bank's response. Users can download the database in a CSV or JSON format. They can also browse the database online and set a filter on each variable discussed above to find complaints regarding a type of product from a specific area against a bank in a date range. The narratives (with consumer consent) were not added to the public database until June 25, 2015.[8] The database includes only complaints against banks under the supervision of the

[7] For example, see "BofA tops financial-complaint list," March 28, 2013, The Wall Street Journal; "CFPB releases expanded complaint database: Three biggest credit unions aboard," March 28, 2013, Credit Union Times; "Expert, research available: Leveraging predictive analytics to avoid CFPB complaint list," March 28, 2013, Business Wire; "Will CFPB complaint database help or humiliate banks?" April 1, 2013, Financial Planning; "CFPB announces massive scope for complaint database," April 1, 2013, American Banker; "Banks roused by the CFPB's database of complaints," April 4, 2013, Bloomberg Businessweek; "The government's new mortgage complaint window is open," April 5, Daily Herald; "Mortgage-related complaints make up almost half of cases in federal database," April 5, 2013, The Washington Post.

[8] On June 25, 2015, the bureau added to the database "narratives for which opt-in consumer consent is obtained and a robust personal information scrubbing standard and methodology has been applied." (CFPB, 2015). To better protect consumer privacy, the CFPB also changed the disclosure of 5-digit ZIP Codes. If the 5-digit ZIP Code area contains fewer than 20,000 people, the bureau discloses the 3-digit ZIP Code, except where the 3-digit ZIP Code area contains fewer than 20,000 people, in which case the bureau does not disclose any ZIP Code data. See Appendix C for two examples of the narratives. We do not examine this event for several reasons. First, the narratives are disclosed only when consumer consent is obtained, creating unknown selection bias. Second, the incremental information of

CFPB (i.e., banks with total assets greater than $10 billion). In other words, complaints about depository institutions with less than $10 billion in assets are referred to the corresponding safety and soundness regulators (e.g., the Federal Deposit Insurance Corporation for state non-member banks), and thus are not included in the database.

2.2 Related Research

Our study relates to three strands of literature. First, finance and marketing research investigates causes and consequences of customer reviews (Chevalier and Mayzlin, 2006; Lee et al., 2015; Fornell et al., 2016; Huang, 2018; Tang, 2018; Liu et al., 2019) and customer grievances specifically (Richins, 1983; Fornell and Wernerfelt, 1987; Conlon and Murray, 1996; Bowman and Narayandas, 2001; Homburg and Furst, 2005; Luo, 2007, 2009; Knox and van Oest, 2014; Ma et al., 2015). Evidence from these studies however is mixed (Fung et al. 2004). Moreover, many unique features of the CFPB complaint database and residential mortgage markets, as discussed in the introduction, make it difficult to extrapolate their findings from other markets (e.g., the restaurant industry as in Jin and Leslie, 2003) to our setting. Studies in this literature also face the challenge of separating the effect of *disclosing* customer feedback from that of underlying product quality. We overcome this challenge by exploiting a shock to the disclosure policy of the CFPB to isolate the effect of disclosure on consumers and banks.

Second, research in consumer finance documents that biases, inattention, and cognitive limitations prevent consumers from making rational choices, leaving a substantial amount of money on the table (e.g., Agarwal et al., 2016, 2017; Alexandrov and Koulayev, 2018). Studies in this literature also explore whether more salient forms of *private* disclosure of key financial terms to individual consumers help them make better decisions, with mixed results (Lacko and Pappalardo, 2007, 2010; Stango and Zinman, 2011, 2014; Navarro-Martinez et al., 2011; Agarwal et al., 2015; Seira et al., 2017; Adams et al., 2021). Our paper differs from those studies in two aspects. (1) We study *public* disclosure, which allows consumers to tap the wisdom of the crowd

narratives is likely to be small relative to the initial publication of the entire database. Third, the reduced granularity of ZIP-code disclosures makes the net effect on the disclosure level unclear.

by browsing the database directly or, more importantly, relying on a marketplace of ideas, such as analysis of the database by third parties (e.g., consumer groups). (2) We examine an intuitive measure of product quality, consumer complaints, as opposed to financial terms (e.g., the annual percentage rate). While the former is relatively easy to understand, it often requires sufficient financial literacy to digest the latter.

Third, three concurrent papers use the CFPB's consumer complaint database to address distinct research questions. Raval (2020) studies which demographic characteristics of a community are associated with higher complaint rates. Hayes et al. (2021) investigate whether the state-level attitude of trust relates to the number of complaints and whether the establishment of the bureau reduces bank fees in low-trust areas. Begley and Purnanandam (2021) find that areas with lower income and educational attainment and a higher share of minorities experience more consumer complaints. They attribute the findings partly to the quantity-focused regulations, such as the Community Reinvestment Act. None of these studies explore the consequences of releasing the complaint database to the public. We also incorporate their findings in our research design by choosing a sample after the establishment of the CFPB (2011-2015) to isolate the effect of disclosure and using county-year fixed effects to strip out the influences of county characteristics.

2.3 Hypothesis Development

It is a priori unclear whether disclosures of mortgage complaints enhance consumer financial protection.[9] Critics point to the fact that the CFPB does not verify complaint contents, draw a random subset of customer experience, or include narratives.[10] Woodward and Hall (2012) and Allen et al. (2013) provide evidence suggesting that consumers do not search effectively in

[9] Notably, we examine only the impact on consumer financial protection and cannot speak to social welfare. While consumers likely benefit from better protection, banks may bear excess costs. In the long run, banks may also benefit from consumers' increased demand due to better protection. Accounting numbers of banks are unable to capture the long-run effects. Future research is necessary to quantify the social effect of this disclosure policy.

[10] For example, Consumer Mortgage Coalition expressed concerns: "the CFPB's complaint information is subjective and unverified, may not be relevant to the complaint, and may not be provided in good faith…the information is not a representative sample of what consumers think...need context to make the data informative to consumers" (Consumer Mortgage Coalition, 2012).

the mortgage market. In light of their findings and consumers' limited capacity to process raw complaint data, they may not be able to incorporate the data into their decisions. Even if consumers fully understand the disclosures, they may not have many alternatives if the local residential mortgage-origination market is dominated by a few banks (Stanton et al., 2014). To the extent that disclosure of mortgage complaints reveals little useful information and thus incurs little consumer response, banks will have few incentives to reduce such complaints (Fung et al., 2004).

On the other hand, several reasons exist why public disclosure can protect consumers. First, before adding a complaint to the public database, the bureau confirms the commercial relationship and consolidates duplicate filings. Second, the public database creates an online word-of-mouth platform, which is more powerful than traditional social learning in aggregating and disseminating the wisdom of crowds (Ellison and Fudenberg, 1995; Chevalier and Mayzlin, 2006; Kremer et al., 2014; Che and Horner, 2018; Bergemann and Bonatti, 2019). Third, individual consumers do not necessarily have to use the database directly. Consumer organizations, researchers, and other third parties can mine the public database and help consumers make more informed decisions (CFPB, 2012).[11] To the extent that these reasons dominate, we expect a greater reduction in mortgage applications to banks that have more mortgage complaints as revealed by the disclosure. The reduction, along with other reputational costs, incentivizes banks to improve on reducing mortgage complaints.[12] Consequently, banks should exhibit faster mean reversion in the number of mortgage

[11] For example, the California Reinvestment Coalition (CRC) states, "CRC has relied on the consumer complaint database as a referral resource for our member organizations to use when their clients face challenges with financial institutions. We also use the database to learn about and to educate the public and regulatory bodies regarding problematic practices and entities, and their prevalence in the marketplace" (CRC, 2018). Another good example is NerdWallet, a personal finance website that helps people make better decisions by comparing financial products from various banks and insurance companies. NerdWallet states, "The six key areas we evaluated include the loan types and loan products offered, online capabilities, online mortgage rate information, customer service and the number of complaints filed with the Consumer Financial Protection Bureau as a percentage of loans issued." (https://www.nerdwallet.com/blog/mortgages/best-mortgage-lenders/).

[12] Beyond the Arc, a data services company, advocates: "There is a silver lining that comes from closely analyzing and tracking complaint data. Banks and credit unions can identify customer issues early on, and take action to improve customer experience" (https://beyondthearc.com/wp-content/media/news/BTA-Q113_Mining-CFPB-Database-to-Improve-Customer-Experience.pdf). Deloitte analyzed the database and issued a report, suggesting that financial companies "use the resulting insights to potentially improve their regulatory compliance effects, customer experience, and their own operational effectiveness" (https://www2.deloitte.com/content/dam/Deloitte/us/Documents/financial-services/us-fsi-cfpb-consumer-complaint-database-091913.pdf). Banks also have incentives to use the database to

complaints after the disclosure. The accelerated mean reversion should be driven by banks with a high number of complaints (i.e., bad performers).

3. Data and Research Design

3.1 Data and Sample Construction

Table 1 outlines the sample selection procedure. We define the unit of analysis as the bank-county-year. We first obtain mortgage applications to banks during 2011-2015 from the HMDA database. Because the complaint database only covers banks under the supervision of CFPB, we restrict our sample to loan applications to these banks (agency code equal to 9 in the HMDA database). The restriction ensures the same regulatory environment for our sample banks as CFPB oversight may impose different effects on CFPB supervised and other banks (Fuster et al., 2021). We match these loan applications to bank identifiers from the Reporter Panel in the HMDA database, which yields 34,048,154 applications to 163 banks. We aggregate the loan application data to the bank-county-year level, resulting in 326,472 observations. We identify at least one mortgage complaint based on the ZIP Codes and bank names in the CFPB's database as of the release date for 32,215 bank-county-years, representing 62 banks.[13] We assign zero for bank-counties without mortgage complaints filed as of the disclosure date. Due to the computing power and time required to estimate a large number of fixed effects in our model, we require that each bank-county-year observation have at least 50 loan originations. We later show that our results are robust to using other cutoffs, such as 30, 70, or 100 annual loan originations. These selection criteria result in a sample of 39,263 bank-county-years, representing 118 banks and 29,151,375 mortgage applications during 2011-2015. Of the 39,263 bank-county-years (118 banks), 18,471

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improve the quality of their mortgage products and services, as they often compare themselves to competitors based on database metrics (CFPB, 2013). Darian Dorsey, Chief of Staff of the CFPB, tells anecdotes about some banks tying executive bonuses to how well the banks respond to complaints (Cortez, 2015).

[13] Most of the complaints are matched to a single county. If a ZIP Code covers multiple counties, we match it to the county with the highest population. Our results are not sensitive to this treatment.

(60) received at least one mortgage complaint.[14] We retrieve bank financial data from the FR Y-9C filings for 105 bank holding companies and from the Call Reports for 13 commercial banks not affiliated with bank holding companies.

3.2 Research Design

To test our hypothesis, we employ a difference-in-differences-in-differences approach to the sample of 39,263 bank-county-year observations. The three-dimensional panel regression is as follows:

$$Y_{i,c,t} = \alpha_{c,t} + \lambda_{i,t} + \mu_{i,c} + \beta_1 \mathit{Mortgage\ Complaint}_{i,c} \times \mathit{Post}_t + \boldsymbol{X}_{i,c,t\text{-}1} + \varepsilon_{i,c,t}, \quad (1)$$

where i indexes banks, c indexes counties, t indexes time, Y is the dependent variable of interest and represents one of the proxies for mortgage applications, α is the county-year fixed effects, λ is the bank-year fixed effects, and μ is the bank-county fixed effects. $\mathit{Mortgage\ Complaint}_{i,c}$ is the number of mortgage complaints filed from county c against bank i as of the disclosure date divided by the number of mortgage originations by the bank in that county in the first year of our sample period (i.e., 2011).[15] We fix the year for the denominator so that the test variable is not affected by the dependent variable (mortgage applications). Post_t is an indicator equal to one for year t that is in or after 2013 and zero otherwise. The HMDA database provides years but not dates of mortgage applications, precluding a finer definition of Post_t by the disclosure date (i.e., March 28, 2013). $\boldsymbol{X}$ is a vector of control variables. In particular, we include the following variables: (1) the fraction of mortgages that are approved by a bank in a county (*Approval Rate*), since higher approval rates may attract more applications (Aiello et al., 2020); (2) an indicator equal to one for brick-and-mortar presence of the bank in the county-year (*Branch Presence*); (3) the log of total deposits collected by the bank's branches in the county-year (*Branch Deposit*). The two branch variables

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[14] Since we start with the CFPB-supervised banks in the HMDA database, the 60 banks with a mortgage complaint as of the release date do not include many well-known banks that are not active in the mortgage market (e.g., State Street Bank and Trust Company, American Express, and GE Capital).

[15] In the primary analysis, we do not allow $\mathit{Mortgage\ Complaint}_{i,c}$ to vary with time to ease the interpretation of β_1 in a traditional triple-differences design. Nevertheless, our inferences are robust to updating $\mathit{Mortgage\ Complaint}_{i,c}$ by year (see Section 4.2).

capture banks' local activities that reduce application costs for consumers. All three variables are lagged by one year to ensure that mortgage applications during the year do not affect the control variables.

Equation (1) essentially represents a difference-in-differences-in-differences specification similar to the one in Gruber (1994). As Gruber (1994) discusses, this triple-differences approach is a powerful research design for identifying causal effects. Essentially, we compare banks with a high number of complaints in a county to banks with a low number of complaints in the same county and measure the change in their relative outcomes around the disclosure, relative to counties in which they receive the same level of complaints. For example, let us consider only two possible values of *Mortgage Complaint*$_{i,c}$: one for banks receiving a high (e.g., above-median) number of complaints from a county as of the disclosure date, and zero otherwise. As shown in Figure 1, Wells Fargo (WFB) received a high number of complaints from McHenry County and Kendall County in Illinois, whereas Bank of America (BOA) received a high number of complaints from McHenry County but not from Kendall County. The triple-differences design allows us to compare the difference between changes in mortgage applications to BOA around the disclosure and those to WFB in McHenry, relative to the difference in Kendall, where they receive the same level of complaints. Appendix A provides a mathematical illustration.[16] As Gruber (1994) notes, the identifying assumption of this approach is fairly weak; it simply requires that there be no systematic contemporaneous local shock that affects the relative outcomes of banks in the same county-year as the complaint release. We cluster standard errors by bank to account for correlated residuals across counties and years within each bank. Our subsequent results are stronger if clustered at the bank-year level.

[16] Notably, we do not argue that individual consumers analyze the database in such a triple-differences fashion (i.e., a consumer calculates the "abnormal" local complaints relative to the average complaints at the bank-year, bank-county, and county-year levels). This empirical model simply requires that the disclosure of local complaints (*Mortgage Complaint*$_{i,c}$×*Post*$_t$) along with other confounding factors (e.g., $\alpha_{c,t}$, $\lambda_{i,t}$, and $\mu_{i,c}$) influences the application choice of an average consumer in that county. The triple-differences specification is designed to strip out the confounding factors and help us uncover the impact of the disclosure (β_1).

3.3 Descriptive Statistics

In Panel A of Table 2, we report descriptive statistics for variables used in the regression analyses. The variable definitions are provided in Appendix B. The median number and dollar amount of mortgage applications across bank-county-years are 290 (= $e^{5.673}$) and \$52,891,610 (= $e^{10.876}\times1000$), respectively. *Mortgage Complaint* has a mean of 0.125. The average approval rate is 71%, and an average bank has at least one branch in 58.6% of county-years. Unsurprisingly, given that CFPB supervises large banks, our sample banks have a median size of \$189 billion in assets (= $e^{19.057}\times1000$). The mean equity and earnings are 11% and 0.9% of total assets. In the average county, 88.3% of the population has a high school diploma (*Education* =1). Panels B and C of Table 2 show the sample distribution by year and state. The proportion of bank-county-year observations with a complaint is stable over time. Each state is well represented, and the three states that generate the most bank-county-year observations with at least one complaint are Florida (1,542), California (1,301), and Ohio (899).

4. Results

4.1 Validation of Mortgage Complaint Disclosures

We begin by examining the information content of mortgage complaints and whether disclosing them reveals new information regarding the quality of mortgage products and services. We calculate the intensity of mortgage complaints as the total number of mortgage complaints as of the disclosure date against a bank divided by the total number of mortgage originations by the bank in 2011 ($Mortgage\ Complaint_i$). We correlate three metrics with $Mortgage\ Complaint_i$. The first two are the number of CFPB enforcement actions against a bank regarding mortgage issues and the total settlement amounts (in millions) in a five-year window after the disclosure of mortgage complaints. We collect the information to calculate the metrics from the CFPB's website for the 118 sample banks. To mitigate the skewness, we take the log of one plus the two variables ($\#Enforcement\ Action_i$ and $\$Settlement_i$). Thirty-four banks were subject to enforcement actions and paid \$3.9 billion in the settlement. The third metric is the customer satisfaction score ($Consumer\ Satisfaction_i$) from *Consumer Reports*, a nonprofit organization known for impartiality and technical expertise in reviewing products (De Langhe et al., 2016).[17] We are able to obtain the scores for 46 of the sample banks. Table 3 Panel A shows that *Mortgage Complaint*$_i$ is significantly positively (negatively) related to *#Enforcement Action*$_i$ and *$Settlement*$_i$ (*Consumer Satisfaction*$_i$). The results reject that null that the complaint data contains no information on the quality of mortgage products and services.

Next, we assess how much incremental information is provided by the release, as perceived by the stock market. This assessment is important as existing word-of-mouth and social media (e.g., Yelp or Google reviews) may preempt the information in the complaint database. Since the timing of disclosure is common for all banks, we use a standard portfolio approach that accounts for the cross-sectional correlation among stock prices (Schipper and Thompson, 1983). A market model is estimated over 100 trading days surrounding the disclosure date:

$$r_t = \alpha + \beta \times r_{m,t} + \gamma \times D_t + \varepsilon_t, \qquad (2)$$

where r_t is portfolio returns of 60 CFPB-supervised public banks (or 320 non-CFPB-supervised public banks); $r_{m,t}$ is daily market returns from the CRSP value-weighted market index; D_t is an indicator variable that equals one for five trading days around the disclosure date: March 28, 2013.

In Table 3 Panel B, we present OLS regression results of estimating equation (2). We find that the coefficient on D_t is negative and statistically significant (two-tailed p-value < 0.05), indicating that the market, on average, reacts negatively to the disclosure of consumer complaints about CFPB banks. Our findings are robust when we use 3, 7, and 10 trading-day windows around the release date (untabulated). In contrast, we find no reaction of non-CFPB supervised banks' stock prices around the release date (two-tailed p-value > 0.1), as the database does not cover them.

To further attribute the finding to the disclosure, we tie the market reactions to the intensity of mortgage complaints disclosed on the event day (*Mortgage Complaint*$_i$). We control for banks' total assets (*Assets*), equity-to-assets ratios (*Equity*), return on assets (*ROA*), and the log of total deposits (*Deposit*), all of which are measured at the end of 2012 for the time-series regressions.

[17] The scores are based on the *Consumer Reports*' 2017 Banking Survey, ranging from 60 to 100. Only the members of *Consumer Reports* have access to the most recent scores (historical scores are unavailable).

Panel C of Table 3 reports portfolio time-series regression results using Sefcik and Thompson's (1986) approach over 360 trading days surrounding the disclosure date. We expand the trading window since we are also interested in whether the relation between the intensity of mortgage complaints and stock returns drifts or reverses in a more extended period.

As shown in the first and second columns of Panel C, we find that a bank's stock returns over the [-2, +2] window is negatively associated with the intensity of mortgage complaints filed as of the release date against the bank (two-tailed p-value < 0.05). We find no association between the stock returns over the [+3, +180] window and the intensity of mortgage complaints, suggesting no over- or under-reaction in the short window surrounding the disclosure date. These findings support the view that the market perceives the disclosure event as a negative shock and responds more negatively when the bank is revealed to have a greater number of mortgage complaints. In sum, our initial evidence confirms the premise that the public disclosure of complaint information conveys negative news, above and beyond existing word-of-month and social media, regarding banks' product and service quality and thus future cash flows.[18] We next turn our attention to its real effect on consumers' mortgage application decisions.

4.2 Primary Results

In Table 4, we present coefficients and t-statistics in parentheses from estimating equation (1). We use the log of both the number and the dollar amount of mortgage applications as the dependent variables and report the results in separate columns.[19] As shown in the first and third columns, we find that *Mortgage Complaint*×*Post* loads significantly negatively (two-tailed p-value < 0.01), a result consistent with the main hypothesis. Regarding the magnitude of the effect, a one standard deviation increase in *Mortgage Complaint* translates into a decrease in the number

[18] Compared with the existing word-of-mouth and social media, the complaint database is more centralized, standardized, user friendly, and veracious (e.g., confirmation of a commercial relationship), allowing more precise assessment of banks' product and service quality.

[19] Internet Appendix Figure A1 shows that taking the log of the number and the dollar amount of mortgage applications effectively reduces the skewness of the raw value.

and total dollar amount of mortgage applications after the disclosure by 10.5% (= 0.164 × 0.640) and 9.1% (= 0.164 × 0.553), respectively.

We interpret the negative coefficient on *Mortgage Complaint×Post* as indicating that the public disclosure of consumer complaints has a real effect on consumers' loan application decisions: applicants are more likely to avoid banks with bad records as disclosed in the complaint database. A possible alternative explanation is that consumers avoid banks with a bad reputation that existed before the public database (perhaps through media or traditional word-of-mouth) and is positively associated with a high number of complaints.[20] To rule out this alternative explanation, we estimate the dynamic effects by interacting each year indicator around the disclosure with *Mortgage Complaint*. As shown in the second and fourth columns of Table 4, we find that the coefficients on *Mortgage Complaint×Year-1* are not statistically different from zero (two-tailed p-value > 0.1). The reduction in mortgage applications occurs in the first year after the public disclosure and persists into the second year (two-tailed p-value < 0.01).[21] It suggests that our finding does not simply reflect consumers' avoidance of banks with a bad reputation that began before the disclosure of the complaint database. Otherwise, we should observe a similar decline in years -1 and 0. We also observe that *Approval Rate* loads positively significantly in columns (2)-(4), consistent with the notion that higher approval rates attract more applications (Aiello et al., 2020).

There are two limitations of using the current measure of the exposure to mortgage complaints, *Mortgage Complaint*$_{i,c}$: (1) it does not vary over time, although the bureau updates the database on a daily basis; (2) it does not capture the exposure at the bank level. We evaluate the importance of these limitations by conducting two additional tests. First, we replace *Mortgage Complaint*$_{i,c}$ with *Mortgage Complaint*$_{i,c,t}$, which is the number of mortgage complaints from

[20] The CFPB enforcement actions and consumer satisfaction scores cannot explain the finding since they are absorbed by the bank-year fixed effects.

[21] We attribute this lack of reaction in the release year (2013) to two primary bases. First, as the database is disclosed near the end of the first quarter of 2013, the variation in mortgage applications during the first quarter adds noise to the dependent variable in 2013. Second, it takes time to impound the complaint information into the actual applications, further reducing the statistical power of detecting consumers' responses in the release year.

county *c* against bank *i* as of March 28 in year *t* divided by the number of mortgage originations by the bank in the county during 2011 through year *t*-1.[22] Note that since the disclosed mortgage complaints began on December 1, 2011, we cannot compute *Mortgage Complaint*$_{i,c,t}$ for the year 2011 and thus exclude that year from the analysis. As shown in Table A3 Panel A of the Internet Appendix, *Mortgage Complaint*$_{i,c,t}$ loads significantly negatively, consistent with consumers' avoidance of banks with a bad reputation in the pre-period. More importantly, *Mortgage Complaint*$_{i,c,t}$×*Post* continues to load significantly negatively, suggesting that the public disclosure *incrementally* influences applications. This result is driven by the reduction in years subsequent to the disclosure, as shown in columns (2) and (4).

Second, we replace *Mortgage Complaint*$_{i,c}$ with *Mortgage Complaint*$_{i}$, which is the total number of mortgage complaints against bank *i* as of the disclosure date, March 28, 2013, divided by the total number of mortgage originations by the bank in 2011. Accordingly, we either drop bank-year fixed effects or use bank fixed effects instead of bank-year and bank-county fixed effects. We also control for bank characteristics. As shown in Table A3 Panel B of the Internet Appendix, the coefficient on *Mortgage Complaint*$_{i}$×*Post* is significantly negative in all specification. In the first column, a one standard deviation increase in *Mortgage Complaint*$_{i}$ translates into a decrease in the number of mortgage applications by 9.5% (= 0.027 × 3.520), which is similar to estimates in Table 4. However, unlike the triple differences design, it is difficult, if not impossible, to rule out the possibility that omitted bank-level variables drive the result. Moreover, to the extent that the quality of mortgage products and services varies across locations/branches within the same bank, *Mortgage Complaint*$_{i}$ contains sizable measurement errors. Thus, this result should be interpreted with caution.

4.3 Sensitivity Tests

We assess the sensitivity of our findings to the initial research design choices. The results are shown in Table A4 of the Internet Appendix.

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[22] We use the cumulative mortgage originations since 2011 as the denominator to accommodate the fact that the numerator, total mortgage complaints as of March 28 in year *t*, is also cumulative.

Alternative samples. We employ a number of alternative samples to examine the sensitivity of our results to the initial sample choice. (1) We construct a “constant sample” in which we include only bank-counties that persist through the entire sample period. (2) We consider a sample of a shorter window around the release of the complaint database, specifically from 2012 to 2014. (3) We require counties to have at least one complaint in a given year to ensure at least one bank with a mortgage complaint in that county-year. Our results are robust to using the three alternative samples.

Alternative measures of mortgage complaints. In the primary analysis, we use the number of mortgage complaints scaled by the number of loan originations in 2011. To examine whether our results are sensitive to this measure of banks’ exposure to mortgage complaints, we use three alternative measures: the log of mortgage complaints, the number of mortgage complaints scaled by the 3-year average of loan originations during 2011-2013, and the number of mortgage complaints scaled by the dollar amount of originated loans. No inferences are affected.

Alternative measures of mortgage applications. We use the number and the dollar amount of mortgage applications as the dependent variable. Since they are not normalized, the findings may be driven by a few large counties. We take the log of these two variables in the primary analyses to address this issue. To further alleviate this concern, we use two market-share measures, based on the number and the dollar amount of mortgage applications within a county-year, as alternative dependent variables. The inferences remain intact.

Alternative cutoffs for sample construction. Previously, we restricted our sample to bank-county-years with at least 50 mortgage originations. To assess whether our results are sensitive to this choice of threshold, we choose different cutoffs. Our results are robust to using the cutoffs of 30, 70, and 100 mortgage originations in a bank-county-year and become even stronger under more aggressive cutoffs.[23]

[23] DeFusco et al. (2020) find that the adoption of the Ability-to-Repay and Qualified Mortgage Rule (ATR/QM) in 2014 under the Dodd-Frank Act significantly reduces the quantity of credit in the jumbo mortgage market. To the extent that the rule is more likely to influence banks that receive more complaints in a local market, this adoption could explain our findings. As the Federal Housing Administration (FHA) insured loans and Veterans Administration (VA) guaranteed loans are exempt from the ATR/QM rule (Fleming, 2013), we use the number of applications for

4.4 Placebo Tests

In equation (1), we estimate the relation between mortgage complaints and applications at the bank-county-year level. Despite the triple-differences design, this relation might be explained by confounding events at the bank-county-year level. For example, a local recession that particularly affects banks with more complaints can reduce mortgage applications to them. To rule out this explanation, we take the log of the number of small business loans originated by bank *i* in county *c* and year *t* ($\textit{Small Business Loans (\#)}_{i,c,t}$) based on banks' Community Reinvestment Act reports, which have been used frequently in the small business lending literature (Dou, 2021). Using $\textit{Small Business Loans (\#)}_{i,c,t}$ as a new dependent variable, we find an insignificant coefficient on *Mortgage Complaint×Post* (two-tailed p-value > 0.1) in Table 5 column (1).

Another confounding event is that independent of the disclosure, local community groups may have waged campaigns in 2013 against banks with bad reputations, which likely received more consumer complaints (about not only mortgages but other financial products) in local areas. The campaigns can provoke customer boycotts, resulting in fewer mortgage applications from those areas to the target banks (California Reinvestment Committee, 2001; Squires, 2003; Dou and Zou, 2019). To rule out this explanation, we explore non-mortgage complaints from the same database. To the extent that the operations of mortgage and non-mortgage segments within a bank are correlated, non-mortgage complaints are likely to capture banks' local reputation in general. We compute the number of credit card complaints and the number of other complaints as of the release date for each bank-county. Both numbers are divided by the number of mortgage originations in 2011, the same denominator used for *Mortgage Complaint*, and then interacted the post indicator with the two variables, respectively. We add the two new interaction terms to equation (1) and re-estimate the equation. Column (2) reports that *Mortgage Complaint×Post* loads significantly negatively after controlling for the release of complaints about credit cards and other products. In contrast, the coefficients on *Credit Card Complaint×Post* and *Other*

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these loans as an alternative dependent variable and continue to find robust results (see Table A5 of the Internet Appendix).

Complaint×*Post* are statistically insignificant (two-tailed p-value > 0.1). Thus, it is the disclosure of mortgage complaints as opposed to broader types of complaints that influence mortgage application decisions. The result weakens the alternative explanation that banks' local reputation combined with community activism drives the findings.

4.5 Matched-pair Design

Banks with distinct characteristics (e.g., size, equity capital, profitability, or deposits) may respond differently to common local market shocks. As such, a potential concern is that the observed results might be driven by the different responses to common local events other than the disclosure of consumer complaints (e.g., Lo, 2015). To mitigate this concern, we construct a matched sample based on observable bank characteristics: banks' total assets (*Assets*), equity-to-assets ratios (*Equity*), return on assets (*ROA*), and the log of total deposits (*Deposit*). We match each bank-county-year observation with a complaint to the observation without a complaint that is in the same county-year and has the closest bank characteristic, imposing a caliper of 2%. We find that the two groups of banks exhibit a statistically insignificant difference in each characteristic after matching on that variable.

We re-estimate equation (1) using each matched sample and report the results in Table 6, where each column presents the result using a matched sample based on the variable indicated in the column header. We find that *Mortgage Complaint*×*Post* loads significantly negatively across all specifications (two-tailed p-value < 0.01). Thus, our findings cannot be attributed to differential responses arising from diverse bank characteristics to local market shocks.

4.6 Cross-sectional Tests

In this section, we test a number of cross-sectional predictions derived from our primary hypothesis that banks with more mortgage complaints in counties exhibit greater reductions in mortgage applications from the counties after the disclosure.

Consumer sophistication. Prior research shows that a disclosure system is more effective when users can better incorporate the disclosed information into their decisions (Fung et al., 2004).

This cross-sectional hypothesis is motivated by the idea that consumers are more likely to act on the information when they are more sophisticated to understand it. As such, we expect a greater reduction in mortgage applications in counties with more sophisticated consumers. We employ a county-level proxy for consumer sophistication: the proportion of the population with a high school diploma (*Education*). The greater the measures, the more sophisticated consumers there are in the county. Prior research has demonstrated that this variable is associated with better financial decisions made by consumers (Stango and Zinman, 2009; Gurun et al., 2016). We define *High* as an indicator equal to one for the observations that have above-median values of this variable and zero otherwise, and then interact it with *Mortgage Complaint*×*Post*. As the first column of Table 7 shows, *Mortgage Complaint*×*Post*×*High* loads significantly negatively (two-tailed p-value < 0.01). This result suggests that greater sophistication helps customers better understand and detect instances of unfair practices from the database, leading to a greater reduction in subsequent loan applications for banks with more mortgage complaints.

Market structure. Our second cross-sectional hypothesis is based on the variation in the market structure. We examine whether consumers' response to mortgage complaints is more pronounced when within-county credit competition is more intense. More alternatives should facilitate the migration of consumers to banks with relatively fewer complaints. We measure credit competition in a county-year using -1×the Herfindahl-Hirschman index based on loan originations (*Competition*). We set the indicator *High* to one for the observations that have above-median values of this variable and zero otherwise, and then interact it with *Mortgage Complaint*×*Post*. The result is reported in the second column of Table 7. As expected, we find that high credit competition strengthens consumers' response, as *Mortgage Complaint*×*Post*×*High* loads significantly negatively (two-tailed p-value < 0.01).

Complaint severity. We next examine whether consumers' reaction varies with complaint severity. To measure severity, we combine two variables available in the complaint database: whether the bank provides monetary or non-monetary relief and whether the consumer disputes the bank's response. Complaints closed with relief or consumer dispute are likely to be more severe than those closed with mere explanations or without dispute. In Appendix C, we provide two examples and conduct textual analysis to validate this claim. We expect a greater reaction of consumers to more severe complaints. We first compute the fraction of complaints tagged with relief or dispute for each bank (*Severity*) and then set the indicator *High* to one for the observations that have above-median values of this variable and zero otherwise. We interact it with *Mortgage Complaint*×*Post*. Consistent with our prediction, *Complaint*×*Post*×*High* loads significantly negatively (two-tailed p-value < 0.05), as shown in the third column of Table 7.[24]

***Information dissemination*.** The evidence so far suggests that disclosure of complaint information influences mortgage applications. Investigating how such information is disseminated and incorporated into consumers' decisions is difficult due to the lack of available data on consumers' behavior before their applications for mortgages. Nevertheless, we provide two pieces of preliminary evidence. First, we compute the state-level change in the Google Search Volume Index (SVI) for the keyword "CFPB" during 12 months before and after the release date (Δ*Google SVI*) and set the indicator *High* to one for the observations in states that have above-median values of Δ*Google SVI* and zero otherwise.[25] As shown in the first column of Table A6 Panel A of the Internet Appendix, *Complaint*×*Post*×*High* loads significantly negatively (two-tailed p-value < 0.05), suggesting that Internet searches by consumers help disseminate the complaint information.

Second, we manually collect comment letters filed by consumer organizations in response to the CFPB's recent inquiry regarding its public reporting practices of consumer complaints.[26] These organizations are aware of the database and likely to use it to help local consumers (see an example from the California Reinvestment Coalition in Section 2.3). For each state, we calculate the number of the consumer groups that are in favor of the public complaint database and have a local branch in that state, scaled by the state's population in 2018 (*Lobbying consumer groups*).

[24] For *Education* and *Competition*, the main effect of *High* and the interaction effect of *High*×*Post* are absorbed by county-year fixed effects. For *Severity*, the main effect of *High* and the interaction effect of *High*×*Post* are absorbed by bank-year fixed effects.

[25] Google tracks users' search volume by search term and location, aggregates search data for each state, and compute the SVI for each state as the ratio of searches from that state to searches from the top state (D.C. for searches for "CFPB").

[26] The inquiry was viewed as a precursor to restricting the public view of the complaint database by the bureau's acting director, Mick Mulvaney (see "Consumer bureau looks to end public view of complaints database," April 25, 2018, The New York Times).

The indicator *High* is set to one for the observations in states that have above-median values of this variable and zero otherwise. As shown in the second column of Table A6 Panel A of the Internet Appendix, *Complaint*×*Post*×*High* loads significantly negatively (two-tailed p-value < 0.01), suggesting that consumer groups play a role in disseminating the complaint information.

5. Tests for the Disciplinary Effect

In this section, we explore the disciplinary effect of the disclosure on banks. The public disclosure of mortgage complaints can create incentives for banks with more complaints to prioritize the quality of mortgage products and services and alleviate problems upfront. This, in turn, should translate into fewer mortgage complaints after the public disclosure. We do not test for changes to the number of complaints around the disclosure; naturally, banks with poorer quality of products and services are more likely to take measures to catch up with the rest of the market absent the public database. This mean-reversion process muddies the relation between the disclosure event and the number of complaints. Instead, we estimate the difference in the coefficient of mean reversion on the number of monthly mortgage complaints before and after the public disclosure.[27] We construct a sample of bank-county-month observations and estimate the following regression:

$$\begin{aligned} \textit{Mortgage Complaint}_{i,c,m+1} = \alpha + \beta_0\, \textit{Mortgage Complaint}_{i,c,m} \\ + \beta_1\, \textit{Mortgage Complaint}_{i,c,m} \times \textit{Post}_m + \varepsilon_{i,c,m}, \end{aligned} \tag{8}$$

where $\textit{Mortgage Complaint}_{i,c,m}$ is the number of mortgage complaints from county c in month m against bank i, scaled by the number of mortgage originations by the bank in the county in that year. We allow the number of originations to vary across years to account for the consumer migration effect. If we use the number of loan originations in 2011 and find a faster mean reversion in *Mortgage Complaint* after the public disclosure, the results might be explained by fewer

[27] We focus on monthly mortgage complaints in order to balance two competing considerations: (1) there is no sufficiently long time-series to estimate the natural mean reversion in the pre-period for annually or quarterly complaints and (2) a discernible improvement in customer experience is likely to take more than a week.

applications to banks with more complaints. $Post_m$ is an indicator equal to one for months in and after March 2013.

Table 8 Panel A provides descriptive statistics for the variable used in the analyses, and Panel B presents the regression results. As shown in the first column, the positive coefficient on *Mortgage Complaint* captures the natural mean revision before the public disclosure, with zero (one) being perfect (no) mean reversion. *Mortgage Complaint*×*Post* loads significantly negatively (two-tailed p-value < 0.01). This result indicates that banks exhibit faster mean reversion in the number of mortgage complaints after the release of information on customer complaints. We then divide the sample between banks whose *Mortgage Complaint* in a county-year is above the median (bad performers) or below the median (good performers). The result is driven by bad performers, as reported in the second and third columns. Since the CFPB's supervision has taken place at the beginning of the pre-period, it is unlikely that the supervision drives the accelerated mean reversion after the disclosure.

A number of cross-sectional tests are conducted for bad performers. We interact *Mortgage Complaint*×*Post* with the three indicators for above-median *Education*, *Competition*, and *Severity*, respectively. We find that the coefficients on the triple interaction terms are negative and statistically significant (two-tailed p-value < 0.01) in Table 8 Panel C. Thus, the increase in the speed of mean reversion varies with the cross-sectional factors as predicted, suggesting that part of the disciplinary effect stems from reactions of consumers in the product market.[28]

6. Conclusion

We analyze the effectiveness of the CFPB's public disclosure of complaints in protecting consumers in mortgage markets. We construct a sample of observations at the bank-county-year level and employ a triple-differences research design. Specifically, county-year, bank-year, and

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[28] We do not include the three sets of fixed effects (bank-month, bank-county, and county-month fixed effects) since such inclusion yields biased parameter estimates in a model with a lagged dependent variable on the right-hand side of the equation (Nickell, 1981; Angrist and Pischke, 2009). Nevertheless, our inferences are unaltered if these fixed effects are added. We also find that the increase in the speed of mean reversion varies with the cross-sectional factors that capture the strength of the information dissemination as predicted (see Table A5 Panel B of the Internet Appendix).

bank-county fixed effects are used to account for local credit demand, bank-specific shocks, and bank-county heterogeneity, respectively. We find a greater reduction in mortgage applications from residents of a county to banks with more mortgage complaints from that county after the disclosure. The effect is stronger in areas with more sophisticated consumers and higher credit competition, as well as for banks with more severe complaints. Banks' number of monthly mortgage complaints exhibits faster mean reversion after the disclosure, and the effect is driven by banks with a high number of mortgage complaints. Together, the findings suggest that by enhancing product market discipline, this public disclosure serves as a useful regulatory tool for consumer financial protection.

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Appendix A: An Illustration of the Triple-differences Design

Equation (1) essentially represents a difference-in-differences-in-differences specification that is similar to the one in Gruber (1994). To better understand this point, consider the following example within a potential outcomes framework (Rubin, 1974). For expositional purposes, we assume there are only two possible values of $Mortgage\ Complaint_{i,c}$: one for banks receiving a high (e.g., above-median) number of complaints from a county as of the disclosure date, and zero otherwise.

Let $Y_{1i,c,t}$ denote the mortgage applications to bank i from county c during period t if the public see a high number of complaints against the bank from that county as of the disclosure date; let $Y_{0i,c,t}$ denote the mortgage applications to bank i from county c during period t if the public see a low number of complaints against the bank from that county. These two variables are referred to as potential outcomes, since it is possible to observe only one or the other, but not both. Assuming that $E[Y_{1i,c,t} - Y_{0i,c,t}|i,c,t]$ is constant and denoted by β_1, bank i's observed mortgage applications can be written as follows:

$$Y_{i,c,t} = \alpha_{c,t} + \lambda_{i,t} + \mu_{i,c} + \beta_1 Mortgage\ Complaint_{i,c} \times Post_t + \varepsilon_{i,c,t}. \tag{A1}$$

Note that this equation is identical to equation (1) but without the control variables for simplicity. According to disclosures on the release date, Wells Fargo (WFB) received a high number of complaints from McHenry County and Kendall County in Illinois, whereas Bank of America (BOA) received a high number of complaints from McHenry County but not from Kendall County. Figure 1 provides an illustration. We can now examine the difference in mortgage applications from Kendall to Wells Fargo around the release of mortgage complaints in 2013 as

$$\begin{aligned} &E[Y_{i,c,t}|i = \text{WFB}, c = \text{Kendall}, t = 2013] - E[Y_{i,c,t}|i = \text{WFB}, c = \text{Kendall}, t = 2012] \\ &\quad = (\alpha_{\text{Kendall, 2013}} - \alpha_{\text{Kendall, 2012}}) + (\lambda_{\text{WFB, 2013}} - \lambda_{\text{WFB, 2012}}) + \beta_1. \end{aligned} \tag{A2}$$

The difference in the mortgage applications from Kendall to Bank of America around the release of mortgage complaints is

$$\begin{aligned} &E[Y_{i,c,t}|i = \text{BOA}, c = \text{Kendall}, t = 2013] - E[Y_{i,c,t}|i = \text{BOA}, c = \text{Kendall}, t = 2012] \\ &\quad = (\alpha_{\text{Kendall, 2013}} - \alpha_{\text{Kendall, 2012}}) + (\lambda_{\text{BOA, 2013}} - \lambda_{\text{BOA, 2012}}). \end{aligned} \tag{A3}$$

Similarly, the difference in mortgage applications from McHenry to Wells Fargo around the release of mortgage complaints in 2013 is

$$\begin{aligned} &E[Y_{i,c,t}|i = \text{WFB}, c = \text{McHenry}, t = 2013] - E[Y_{i,c,t}|i = \text{WFB}, c = \text{McHenry}, t = 2012] \\ &\quad = (\alpha_{\text{McHenry, 2013}} - \alpha_{\text{McHenry, 2012}}) + (\lambda_{\text{WFB, 2013}} - \lambda_{\text{WFB, 2012}}) + \beta_1. \end{aligned} \tag{A4}$$

The difference in the mortgage applications from McHenry to Bank of America around the release of mortgage complaints is

$$\begin{aligned} &E[Y_{i,c,t}|i = \text{BOA}, c = \text{McHenry}, t = 2013] - E[Y_{i,c,t}|i = \text{BOA}, c = \text{McHenry}, t = 2012] \\ &\quad = (\alpha_{\text{McHenry, 2013}} - \alpha_{\text{McHenry, 2012}}) + (\lambda_{\text{BOA, 2013}} - \lambda_{\text{BOA, 2012}}) + \beta_1. \end{aligned} \tag{A5}$$

Each of the four equations above (i.e., (A2)-(A5)) represents the first difference. The second difference (i.e., difference-in-differences) becomes:

$$(A2) - (A3) = (\lambda_{\text{WFB, 2013}} - \lambda_{\text{WFB, 2012}}) - (\lambda_{\text{BOA, 2013}} - \lambda_{\text{BOA, 2012}}) + \beta_1, \text{ and}$$

$$(A4) - (A5) = (\lambda_{\text{WFB, 2013}} - \lambda_{\text{WFB, 2012}}) - (\lambda_{\text{BOA, 2013}} - \lambda_{\text{BOA, 2012}}).$$

Finally, the third difference (i.e., difference-in-differences-in-differences) is:

$$[(A2) - (A3)] - [(A4) - (A5)] = \beta_1. \tag{A6}$$

Thus coefficient β_1 can capture the effect of releasing a high number of mortgage complaints on subsequent mortgage applications. The conventional difference-in-differences design relies on the parallel trends assumption (i.e., $(\lambda_{\text{WFB, 2013}} - \lambda_{\text{WFB, 2012}}) - (\lambda_{\text{BOA, 2013}} - \lambda_{\text{BOA, 2012}}) = 0$), whereas the triple differences can uncover β_1 without such an assumption.

Appendix B: Variable Definitions

This table lists detailed definitions of variables used in our analyses.

Variables	Definitions	Source
Mortgage Application (#)$_{i,c,t}$	Log of the number of mortgage applications to bank *i* in county *c* and year *t*.	HMDA database
*Mortgage Application ($)*$_{i,c,t}$	Log of the total dollar amount (in thousands) of mortgage applications to bank *i* in county *c* and year *t*.	HMDA database
Mortgage Complaint$_{i}$	The total number of mortgage complaints against bank *i* as of the disclosure date divided by the number of mortgage originations of the bank in 2011.	CFPB Complaint / HMDA database
Mortgage Complaint$_{i,c}$	The number of mortgage complaints in county *c* against bank *i* as of the disclosure date divided by the number of mortgage originations of the bank in the county in 2011.	CFPB Complaint / HMDA database
Post$_{t}$	An indicator equal to one for years in and after 2013, and zero otherwise.	HMDA database
Approval Rate$_{i,c,t\text{-}1}$	The fraction of mortgage applications to bank *i* in county *c* that are approved in year *t*-1.	HMDA database
Branch Presence$_{i,c,t\text{-}1}$	An indicator equal to one for the presence of a branch of bank *i* in county *c* and year *t*-1, and zero otherwise.	FDIC Summary of Deposits
Branch Deposit$_{i,c,t\text{-}1}$	Log of total deposits collected by bank *i*'s branches in county *c* and year *t*-1, and zero otherwise.	FDIC Summary of Deposits
Assets$_{i,t}$	Log of total assets (RCFD2170 for commercial banks or BHCK2170 for bank holding companies) for bank *i* by the end of year *t*.	Y-9C/ Call Reports
Equity$_{i,t}$	Total equity divided by total assets (RCFD3210/RCFD2170 for commercial banks or BHCK3210/BHCK2170 for bank holding companies) for bank *i* by the end of year *t*.	Y-9C/ Call Reports
ROA$_{i,t}$	Net income divided by total assets (RIAD4300/ RCFD2170 for commercial banks or BHCK4300/BHCK2170 for bank holding companies) for bank *i* in year *t*.	Y-9C/ Call Reports
Deposit$_{i,t}$	Log of total deposits (RCON2200 for commercial banks or BHDM6631 + BHDM6636 for bank holding companies) for bank *i* by the end of year *t*.	Y-9C/ Call Reports
Education$_{c}$	The proportion of the population with a high school diploma in county *c* measured in 2012.	2012 American Community Survey
Competition$_{c}$	-1×the Herfindahl-Hirschman Index (HHI), calculated as the sum of the squared market share of each bank's mortgage originations in county *c* measured in 2012.	HMDA database

Severity$_i$	The fraction of mortgage complaints tagged with relief or consumer dispute against bank *i*.	CFPB Complaint database
High	An indicator equal to one for counties that have the above-median levels of *Education* and *Competition*, respectively, and for banks that have the above-median level of *Severity*.	
Mortgage Complaint $_{i,c,m}$	The number of mortgage complaints against bank *i* in county *c* and month *m* divided by the number of mortgage originations of the bank in the county in that year.	CFPB Complaint / HMDA database
Post$_m$	An indicator equal to one for months in and after March 2013, and zero otherwise.	CFPB Complaint database

Appendix C: Validation of the Complaint Severity Measure

In this appendix, we validate our measure of complaint severity by conducting a textual analysis of consumer narratives from individual complaints. Since consumer narratives were unavailable upon the public release of mortgage complaints in 2013, the only way to assess the severity of each complaint is to identify whether complaints were tagged with negative attributes by the CFPB. The most pertinent complaint attributes are how the company responded to the complaint (i.e., providing monetary or non-monetary relief vs. explanation) and whether the consumer disputed the response. We posit that consumers perceive complaints to be more severe if they are tagged with either "closed with relief" or "consumer disputed" than those without any relief/dispute.

Starting on June 25, 2015, the CFPB added consumer narratives (with their consent) to the complaint database on a daily basis, allowing us to validate our measure of complaint severity. We randomly draw 3,000 mortgage complaint narratives filed in 2015. 36% of complaints are tagged with either relief or consumer dispute. We construct seven metrics using textual analysis of the narratives and associate these metrics with the presence of relief or dispute. Exhibit C1 reports the results. Exhibit C2 shows two examples in the CFPB database.

We first compare the number of words in narratives between complaints with and without relief or dispute. Narratives of complaints with relief or dispute on average contain 274 words, while those without such attributes contain 252 words. The difference is significant at the 1% level. We also find that narratives of complaints with relief or dispute have more personal information, which is scrubbed by the CFPB, and more quantitative information, which is bracketed by the CFPB, although the second difference is statistically insignificant. We then examine the content of narratives by using sentiment dictionaries on Loughran-McDonald's website (https://sraf.nd.edu/textual-analysis/resources/). We find that narratives of complaints tagged with relief or dispute on average contain significantly greater constraining, litigious, and negative words. Finally, we calculate the tone of each narrative, as measured by positive minus negative words divided by the total word count, and find that the tone of complaints with relief or dispute is significantly more negative. Overall, these results support that complaints with relief or dispute are more severe than others.

Exhibit C1: Relief/dispute and complaint severity based on textual analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Relief/dispute	*Words*	*Personal*	*Quant*	*Constrain*	*Litigious*	*Negative*	*Tone*
1 (N=1,076)	273.96	10.72	1.13	0.974	2.842	11.09	-0.043
0 (N=1,924)	251.83	9.19	1.094	0.772	2.356	10.00	-0.040
Difference	22.12***	1.53***	0.036	0.202***	0.486***	1.09***	-0.003*

Exhibit C2: Two examples of consumer complaint narratives in 2015

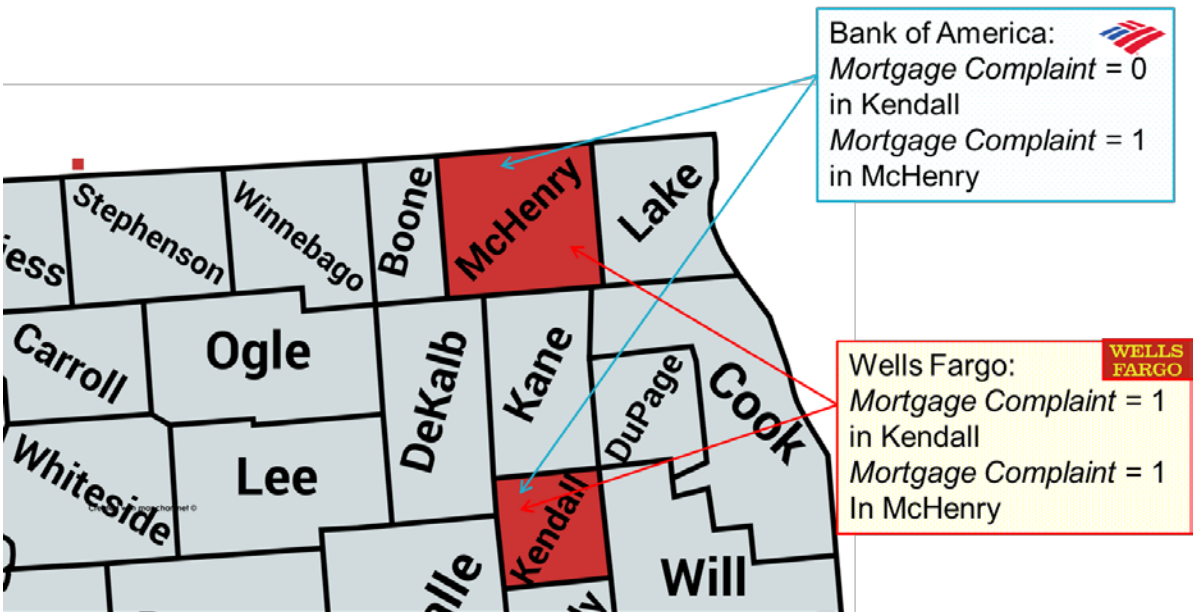
Date CFPB received the complaint	3/29/2015
Consumer's state	FL
Consumer's ZIP	[blank]
Submitted via	Web
Tags	[blank]
Did consumer dispute the response?	Yes
Product	Mortgage
Sub-product	Conventional adjustable mortgage (ARM)
Issfue	Loan modification,collection,foreclosure
Consumer consent to publish narrative	Consent provided
Consumer complaint narrative	On XXXX XXXX XX/XX/XXXX after several months of paperwork we closed on our home with XXXX WHOLESALE CORPORATION. I was asked to sign hundreds of papers with little or no time to review any of them. At that moment I was pressured to get the closing done. We provided 10 % of the value of our home and our mortgage was {$1400.00} plus a MIP of {$390.00} or {$1800.00} per month with an interest rate of 2.5 %. By the end of the fifth year payments blew up to {$2800.00} plus {$390.00} of MIP to {$3200.00} per month. Just the

A Clear Violation of The Home Ownership and Equity Protection Act (HOEPA) Rule: "Creditors and mortgage brokers are prohibited from recommending default on an existing loan to be refinanced by a high-cost mortgage (§ 1026.34(a)(6) and comments 34(a)(6)-1 and 2)."

	mortgage grew 127.20 %. During that process XXXX sold our mortgage to several other banks including CountryWide Home Loans and Bank of America. Before the 127.20 % increase in our mortgage payment came through we requested Bank of America to refinance and their response every time was " you are paying on time we ca n't help you ''. We kept on calling until XXXX Bank of America representative stated that the reason they were unable to help us was because we were current with our payments and we needed to be in default for them to be able to help ''. Based on those instructions we defaulted and 60 days later re-applied through the Home Affordable Refinance Act XXXX times. Even thou we fulfilled 100 % of the criteria BOA refused to refinance and proceeded with a foreclosure. Since we found the whole situation building up against us we hired an attorney and we did a compliance stress test of our mortgage with a certified reputable Loan Analyst for the RESPA and TILA and the result stated that the mortgage generator and its successors violated many RESPA and TILA federal and state statutes. We filed a counter claim at the court stating that not only the mortgage note are unforceable due to direct violations of TILA but also of the HOEPA and failed to deliver a notice of acceleration to us the homeowners violating the Federal Debt Collection Practices Act and also Bank of America breached the mortgage agreement by force placed insurance in an amount in excess of that required under the mortgage. The mortgage also understated the finance charges and annual percentage rate violating the Truth in Lending Disclosure Statement at the time of closing. To top all that we requested a Home Equity Line of Credit for {$100000.00} which Bank of America provided even though our home did n't have enough equity. Throwout the life of the HELOC we paid it in full several times and Bank of America kept on lending us money even there was not equity to support that loan also known as predatory lending practices. Even after Bank of America tries to foreclose in our primary residency and put our family on the street, we made and arrangement to pay the {$110000.00} HELOC and we satisfied that mortgage on XXXX XXXX XX/XX/XXXX
Date complaint sent to company	4/2/2015
Company name	BANK OF AMERICA, NATIONAL ASSOCIATION
Timely response?	Yes
Company response to consumer	Closed with non-monetary relief
Company public response	Company chooses not to provide a public response
Date CFPB received the complaint	5/4/2015
Consumer's state	IL
Consumer's ZIP	600XX
Submitted via	Web
Tags	[blank]
Did consumer dispute the response?	No
Product	Mortgage
Sub-product	Conventional adjustable mortgage (ARM)
Issue	Loan modification,collection,foreclosure
Consumer consent to publish narrative	Consent provided
Consumer complaint narrative	I am an unemployed mother who owns a condo rental property. The condo was involved in a fire that originated in an above unit and was destroyed as a result. Unfortunately I lost my renter and am unable to pay my mortgage. The property has depreciated considerably from the time I purchased it. The unit is down to the studs now and is worth even less. When I contacted Wells Fargo to negotiate a reasonable short payment I was denied by the legal department. I feel like I am being taken advantage of by Wells Fargo Bank.

Date complaint sent to company	5/4/2015
Company name	WELLS FARGO & COMPANY
Timely response?	Yes
Company response to consumer	Closed with explanation
Company public response	Company chooses not to provide a public response

Figure 1: An Illustration of the Triple-differences Design



This figure provides an example to illustrate the triple-differences identification strategy. For expositional purposes, we assume there are only two possible values of *Mortgage Complaint*$_{i,c}$: one for banks receiving a high (above-median) number of complaints from a county as of the disclosure date, and zero otherwise. According to disclosures on the release date, Wells Fargo (WFB) received a high number of complaints from McHenry County and Kendall County in Illinois, whereas Bank of America (BOA) received a high number of complaints from McHenry county but not from Kendall County. The triple-differences design allows us to compare the difference between the change in mortgage applications to BOA around the disclosure and that to WFB in McHenry, relative to the difference in Kendall, where they receive the same level of complaints.

Table 1: Sample Selection

Selection criteria	Bank Level: Total obs.	Bank Level: Obs. with a complaint	Bank-county-year Level: Total obs.	Bank-county-year Level: Obs. with a complaint	Application Level: Total mortgage applications
(1) CFPB banks during 2011-2015 from the HMDA database	163		326,472		34,048,154
(2) Merge with CFPB complaint database as of the disclosure date		62		32,215	
(3) Exclude bank-counties if annual mortgage originations < 50	(45)	(2)	(287,209)	(13,744)	(4,896,779)
Final sample	118	60	39,263	18,471	29,151,375

This table shows the sample selection criteria. We restrict our sample to banks under the supervision of the Consumer Financial Protection Bureau (CFPB) for the period from 2011 to 2015. We also require that bank-county observations have at least 50 loan originations per year.

Table 2: Descriptive Statistics

Panel A: Summary statistics (Bank-county-year observations)

Variable	N	Mean	Std.	Q1	Median	Q3
Mortgage Application (#)	39263	5.873	1.030	5.100	5.673	6.446
Mortgage Application ($)	39263	11.064	1.200	10.186	10.876	11.761
Mortgage Complaint	39263	0.125	0.164	0.000	0.000	0.222
Post	39263	0.537	0.499	0.000	1.000	1.000
Approval Rate	39263	0.707	0.179	0.656	0.743	0.811
Branch Presence	39263	0.586	0.493	0.000	1.000	1.000
Branch Deposit	39263	7.296	6.241	0.000	10.948	12.564
Assets	39263	18.121	5.173	17.813	19.057	21.246
Equity	39263	0.110	0.041	0.102	0.112	0.125
ROA	39263	0.009	0.007	0.005	0.009	0.013
Deposits	39263	17.583	5.008	17.163	18.701	20.563
Education	39263	0.883	0.050	0.861	0.892	0.917
Competition	39263	-0.094	0.045	-0.117	-0.088	-0.063
Severity	39263	0.303	0.150	0.267	0.314	0.400

Panel B: Sample distribution by mortgage application year

Mortgage application year	Obs. with a complaint	Obs. without complaint
2011	3827	4809
2012	4320	5229
2013	4241	4810
2014	3113	2857
2015	2970	3087
Total	18471	20792

Panel C: Sample distribution by state

State	Obs. with a complaint	Obs. without complaint	State	Obs. with a complaint	Obs. without complaint
Alabama	282	563	Montana	74	86
Alaska	27	42	Nebraska	106	142
Arizona	268	219	Nevada	129	99
Arkansas	100	396	New Hampshire	148	95
California	1301	1221	New Jersey	762	477
Colorado	446	620	New Mexico	140	112
Connecticut	287	184	New York	767	651
District of Columbia	114	77	North Carolina	848	1260
Delaware	53	41	North Dakota	26	54
Florida	1542	904	Ohio	899	877
Georgia	869	757	Oklahoma	115	281
Hawaii	76	57	Oregon	316	337
Idaho	119	167	Pennsylvania	766	876
Illinois	482	556	Rhode Island	93	90
Indiana	361	622	South Carolina	394	498
Iowa	112	204	South Dakota	26	77
Kansas	128	189	Tennessee	394	506
Kentucky	204	397	Texas	879	1152
Louisiana	261	382	Utah	133	253
Maine	88	87	Vermont	35	61
Maryland	589	404	Virginia	778	976

Massachusetts	366	340	Washington	464	496
Michigan	665	549	West Virginia	69	215
Minnesota	356	396	Wisconsin	454	493
Mississippi	94	346	Wyoming	31	54
Missouri	361	513	Puerto Rico	74	341
			Total	18471	20792

Panel A presents descriptive statistics of variables used in our analyses. *Mortgage Application (#)* is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Application ($)* is the log of the total dollar amount (in thousands) of mortgage applications to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for years in and after 2013. *Approval Rate* is the mortgage approval rate of a bank in a county in year *t*-1. *Branch Presence* is an indicator equal to one for the presence of a branch of the bank in the county in year *t*-1. *Branch Deposits* is the log of total deposits collected by a bank's branches in a given county in year *t*-1. *Assets* is the log of total assets. *Equity* is total equity divided by total assets. *ROA* is earnings divided by total assets. *Deposits* is the log of total deposits. *Education* is the proportion of the population with a high school diploma in a county measured in 2012. *Competition* is -1×the Herfindahl-Hirschman Index (HHI) of mortgage originations in a county. *Severity* is the fraction of mortgage complaints tagged with relief or consumer dispute at the bank level. Detailed variable definitions and data sources are presented in Appendix B. Panel B (Panel C) shows sample distribution by mortgage application year (state).

Table 3: Validation of Mortgage Complaint Disclosures

Panel A: Cross-sectional regressions

Dependent variable =	(1) *# Enforcement Action*	(2) *$Settlement*	(3) *Consumer Satisfaction*
Mortgage Complaint$_i$	3.853***	21.510***	-44.227***
	(3.51)	(4.75)	(-2.91)
Observations	118	118	46
R^2	0.0958	0.1630	0.1611

Panel B: Market reaction to the disclosure event

	(1) CFPB Banks	(2) Non-CFPB Banks
Dependent variable =	r_t	
Intercept	0.001	0.001*
	(1.61)	(1.87)
$r_{m,t}$	1.224***	1.291***
	(17.78)	(23.52)
D_t	-0.005**	-0.002
	(-2.03)	(-1.23)
R^2	0.768	0.849

Panel C: The relation between market reaction and mortgage complaints

Window =	(1) *CAR* [–2, +2]	(2) *CAR* [–2, +2]	(3) *CAR* [+3, +180]	(4) *CAR* [+3, +180]
Intercept	-0.003	-0.003	0.000	0.002
	(-1.06)	(-0.20)	(0.70)	(0.79)
Mortgage Complaint$_i$	-0.006**	-0.006**	0.000	0.000
	(-1.99)	(-2.07)	(0.80)	(1.33)
Assets		-0.000		-0.000
		(-0.00)		(-0.44)
Equity		0.055		0.653
		(0.09)		(0.14)
ROA		-0.037		-0.002
		(-0.35)		(-0.12)
Deposits		0.000		0.000
		(0.039)		(0.11)

This table presents the results of the validation of mortgage complaint disclosures. Panel A provides coefficients and corresponding t-statistics estimated from cross-sectional regressions of the dependent variables shown in each column header on the independent variables listed. *#Enforcement Action* is the log of one plus the number of the CFPB's enforcement actions taken against the bank over the five years after the disclosure date. *$Settlement* is log of the total amount (in millions) of the settlement from the enforcement actions. *Consumer Satisfaction* is consumers' overall satisfaction score with their banks, surveyed by *Consumer Reports*, ranging from 60 to 100. *Mortgage Complaint* is the number of mortgage complaints against bank *i* as of the disclosure date, March 28, 2013, divided by the number of mortgage originations by the bank in 2011. Panel B reports average market reactions for CFPB-supervised and non-CFPB banks around the disclosure date, when CFPB released previously collected mortgage complaints to the public.

Non-CFPB banks include bank holding companies, thrift holding companies, commercial banks, and thrifts that are not supervised by CFPB. The coefficients are estimated using the following market model over 100 trading days surrounding the disclosure date.

$$r_t = \alpha + \beta * r_{m,t} + \gamma * D_t + \varepsilon_{\mathrm{t}}$$

where r_t is portfolio returns of CFPB-supervised (or non-CFPB) banks, $r_{m,t}$ is daily market returns of the CRSP value-weighted market index, and D_t is an indicator variable equal to one for 5 trading days around the disclosure date. Panel C reports the Sefcik and Thompson (1986) portfolio time-series regression results for CFPB-supervised banks over the 360 trading days surrounding the disclosure date. *CAR* is the cumulative abnormal returns over the trading windows indicated in the header. *Mortgage Complaint*$_i$ is the number of mortgage complaints as of the disclosure date against a bank divided by the number of mortgage originations by the bank in 2011. *Assets* is the log of total assets, *Equity* is total equity divided by total assets, *ROA* is earnings divided by total assets, and *Deposits* is the log of total deposits, all of which are measured at the end of 2012 for the time-series regression. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table 4: Effect of Mortgage Complaint Disclosure on Mortgage Applications

	(1)	(2)	(3)	(4)
Dependent variable =	*Mortgage Application (#)*$_{i,c,t}$		*Mortgage Application (\$)*$_{i,c,t}$	
Mortgage Complaint$_{i,c}$ × *Post*$_t$	-0.640***		-0.553***	
	(-5.51)		(-4.89)	
Mortgage Complaint$_{i,c}$ × *Year -1*		0.013		0.064
		(0.07)		(0.37)
Mortgage Complain t$_{i,c}$ × *Year 0*		-0.066		-0.026
		(-0.37)		(-0.16)
Mortgage Complaint$_{i,c}$ × *Year 1*		-1.042***		-0.922***
		(-5.07)		(-4.43)
Mortgage Complaint$_{i,c}$ × *Year 2*		-1.027***		-0.819***
		(-4.76)		(-3.70)
Approval Rate$_{i,c,t-1}$	0.156	0.177*	0.210**	0.228***
	(1.62)	(1.92)	(2.32)	(2.70)
Branch Presence$_{i,c,t-1}$	0.017	-0.048	0.022	-0.142
	(0.87)	(-0.24)	(1.31)	(-0.83)
Branch Deposit$_{i,c,t-1}$	-0.029	0.018	-0.125	0.023
	(-0.15)	(0.94)	(-0.72)	(1.39)
Bank-year FE	Yes	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes
Observations	39263	39263	39263	39263
R^2	0.7524	0.7619	0.6975	0.7049

This table reports the effect of mortgage complaint disclosure on mortgage applications. The coefficients and corresponding t-statistics are estimated from pooled regressions of the dependent variables shown in each column header on the independent variables listed. *Mortgage Application (#)* is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Application ($)* is the log of the total dollar amount (in thousands) of mortgage applications to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for years in and after 2013. *Approval Rate* is the mortgage approval rate of a bank in a county in year *t*-1. *Branch Presence* is an indicator equal to one for the presence of a branch of the bank in the county in year *t*-1. *Branch Deposits* is the log of total deposits collected by a bank's branches in a given county in year *t*-1. *Year X*'s are indicators that capture the years prior to, during, and subsequent to the year of 2013 (*Year 0* = 1 for 2013). Bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table 5: Placebo Tests

	(1)	(2)
Dependent variable =	*Small Business Loans (#)*$_{i,c,t}$	*Mortgage Application (#)*$_{i,c,t}$
Mortgage Complaint$_{i,c}$×*Post*$_t$	0.068	-0.599***
	(0.75)	(-4.63)
Credit Card Complaint$_{i,c}$×*Post*$_t$		0.018
		(0.18)
Other Complaint$_{i,c}$×*Post*$_t$		-0.136
		(-1.34)
Baseline Controls	Yes	Yes
Bank-year FE	Yes	Yes
Bank-county FE	Yes	Yes
County-year FE	Yes	Yes
Bank clustering	Yes	Yes
Observations	39263	39263
R^2	0.5268	0.7525

This table reports two placebo tests. The coefficients and corresponding t-statistics in parentheses are estimated from pooled regressions of the dependent variables shown in each column header on the independent variables listed. In column (1), *Small Business Loans (#)* is the log of the number of small business loans originated by a bank in a county-year. In column (2) *Mortgage Application (#)* is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Credit Card Complaint* is the number of credit card complaints as of the disclosure date from a county against a bank and *Other Complaint* is the number of other complaints as of the disclosure date from a county against a bank, both of which are divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for mortgage application years in and after 2013. The baseline control variables, bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table 6: Matched-pair Design

Panel A: Matched sample characteristics

	(1) Obs. with a complaint Mean	(2) Obs. without complaint Mean	(3) Differences (1) – (2)	(4) t-stats
Assets	19.435	19.407	0.028	1.00
Equity	0.115	0.115	0.000	1.19
ROA	0.010	0.010	0.000	0.49
Deposit	18.788	18.763	0.025	0.82

Panel B: Matched sample regression

Dependent variable =	*Mortgage Application (#)$_{i,c,t}$*			
	(1)	(2)	(3)	(4)
Matched on =	*Assets*	*Equity*	*ROA*	*Deposit*
Mortgage Complaint$_{i,c}$×Post$_t$	-0.268***	-0.556***	-0.863***	-0.354***
	(-2.76)	(-3.23)	(-4.15)	(-3.93)
Baseline Controls	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes
Observations	11736	7394	5968	8554
R^2	0.7699	0.6911	0.6554	0.7524

This table presents the effect of mortgage complaint disclosure on mortgage application using four matched samples of bank-county-years with and without complaints based on *Assets*, *Equity*, *ROA*, and *Deposit*, respectively. For each bank-county-year with a mortgage complaint, we select a bank-county-year without mortgage complaints in the same county-year and with the closest bank characteristic, imposing a caliber of 2%. Panel A presents the mean of bank characteristics by affected and unaffected observations, the differences, and corresponding t-statistics. In Panel B, *Mortgage Application (#)* is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for years in and after 2013. The matching bank characteristic is indicated in each column header. The baseline control variables, bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table 7: Cross-Sectional Analyses

Dependent variable =	*Mortgage Application (#)$_{i,c,t}$*		
	(1)	(2)	(3)
Partitioning variable =	*Education$_c$*	*Competition$_c$*	*Severity$_i$*
Mortgage Complaint$_{i,c}$×Post$_t$	-0.487***	-0.473***	-0.295*
	(-3.29)	(-3.63)	(-1.92)
Mortgage Complaint$_{i,c}$×Post$_t$×High	-0.248***	-0.543***	-0.604***
	(-3.24)	(-5.25)	(-3.72)
Baseline Controls	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes
Observations	39263	39263	39263
R^2	0.7527	0.7542	0.7535

This table reports the effect of mortgage complaint disclosure on mortgage applications conditional on three partitioning variables. *Mortgage Application* (#) is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for mortgage application years in and after 2013. *Education* is the proportion of the population with a high school diploma in a county measured in 2012. *Competition* is -1×the Herfindahl-Hirschman Index (HHI) of mortgage originations in a county. *Severity* is the fraction of mortgage complaints tagged with relief or consumer dispute. *High* is an indicator equal to one for counties that have the above-median levels of *Education* and *Competition*, respectively, and for banks that have the above-median level of *Severity*. The baseline control variables, bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table 8: Disciplinary Effects

Panel A: Descriptive statistics

Variable	N	Mean	Std.	Q1	Median	Q3
Mortgage Complaint$_{i,c,m}$	72947	0.114	0.108	0.000	0.120	0.187
Mortgage Complaint$_{i,c,m+1}$	72947	0.109	0.110	0.000	0.113	0.188
Education	72947	0.885	0.046	0.864	0.892	0.916
Competition	72947	-0.093	0.039	-0.114	-0.089	-0.066
Severity	72947	0.232	0.080	0.181	0.200	0.259

Panel B: Regression analyses

Dependent variable =	*Mortgage Complaint*$_{i,c,m+1}$		
	(1) Full Sample	(2) Bad Performers	(3) Good Performers
Mortgage Complaint$_{i,c,m}$	0.465***	0.752***	0.363***
	(7.08)	(13.76)	(12.71)
Mortgage Complaint$_{i,c,m}$×*Post*$_m$	-0.092***	-0.114***	-0.030
	(3.04)	(-5.48)	(-1.49)
Bank clustering	Yes	Yes	Yes
Observations	72947	36730	36217
R^2	0.1584	0.2144	0.0369

Panel C: Cross-sectional analyses – Bad Performers Only

Dependent variable =	*Mortgage Complaint*$_{i,c,m+1}$		
	(1)	(2)	(3)
Partitioning variable =	*Education*	*Competition*	*Severity*
Mortgage Complaint$_{i,c,m}$	0.729***	0.734***	0.748***
	(12.58)	(12.95)	(13.02)
Mortgage Complaint$_{i,c,m}$ ×*Post*$_m$	-0.007	-0.053*	-0.036
	(-0.22)	(-1.95)	(-1.04)
Mortgage Complaint$_{i,c,m}$ ×*Post*$_m$×*High*	-0.192***	-0.139***	-0.203***
	(-5.84)	(-8.15)	(-3.89)
Bank clustering	Yes	Yes	Yes
Observations	36730	36730	36730
R^2	0.2208	0.2208	0.2261

Panel A reports descriptive statistics of variables used in tests for disciplinary effects. The unit of analysis is at the bank-county-month level. Panel B presents the regression results using the full sample and the subsamples based on the level of mortgage complaints. Bad (Good) Performers are banks that have the above-median (below-median) level of *Mortgage Complaint*$_{i,c,m}$ in each county and year. *Mortgage Complaint*$_{i,c,m}$ is the number of monthly mortgage complaints against a bank in a county in month *m* scaled by the number of mortgage originations by the bank in the county in that year. *Post*$_m$ is an indicator equal to one for year-months in and after March 2013. Panel C presents the regression results using bad performers only conditional on three partitioning variables. *Education* is the proportion of the population with a high school diploma in a county measured in 2012. *Competition* is -1×the Herfindahl-Hirschman Index (HHI) of mortgage originations in a county. *Severity* is the fraction of mortgage complaints tagged with relief or consumer dispute at the bank level. *High* is an indicator equal to one for counties that have the above-median levels of *Education* and *Competition*, respectively, and for banks that have the above-median level of *Severity*.

Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Internet Appendix

Public Disclosure and Consumer Financial Protection

This appendix provides supplemental materials that support the manuscript "Public Disclosure and Consumer Financial Protection."

Table A1: Effect of Mortgage Complaint Disclosure on Mortgage Applications – Alternative Definitions of Local Markets

Panel A: Analysis at the bank-ZIP-year level

	(1)	(2)
Dependent variable =	*Mortgage Application (#)*	*Mortgage Application ($)*
Mortgage Complaint×Post	-0.507***	-0.429***
	(-8.71)	(-6.20)
Approval Rate	0.126	0.111**
	(1.55)	(2.10)
Branch Deposit	0.033	0.039
	(1.25)	(0.72)
Branch Presence	-0.675**	-0.783
	(-2.36)	(-1.21)
Bank-year FE	Yes	Yes
Bank-ZIP FE	Yes	Yes
ZIP-year FE	Yes	Yes
Bank clustering	Yes	Yes
Observations	44808	44808
R^2	0.8105	0.7346

Panel B: Analysis at the bank-MSA-year level

	(1)	(2)
Dependent variable =	*Mortgage Application (#)*	*Mortgage Application ($)*
Mortgage Complaint×Post	-0.519***	-0.496***
	(-6.60)	(-7.08)
Approval Rate	-0.097	-0.078
	(-0.50)	(-0.42)
Branch Deposit	0.003	-0.000
	(0.28)	(-0.02)
Branch Presence	-0.117	-0.048
	(-0.73)	(-0.28)
Bank-year FE	Yes	Yes
Bank-MSA FE	Yes	Yes
MSA-year FE	Yes	Yes
Bank clustering	Yes	Yes
Observations	20502	20502
R^2	0.7246	0.6776

Panel C: Analysis at the bank-state-year level

	(1)	(2)
Dependent variable =	*Mortgage Application (#)*	*Mortgage Application ($)*
Mortgage Complaint×Post	-0.356***	-0.212*
	(-3.19)	(-1.90)
Approval Rate	-0.038	-0.245
	(-0.22)	(-1.29)
Branch Deposit	0.041***	0.028***
	(3.31)	(2.77)
Branch Presence	-0.165	-0.054
	(-1.10)	(-0.42)
Bank-year FE	Yes	Yes
Bank-state FE	Yes	Yes
State-year FE	Yes	Yes
Bank clustering	Yes	Yes
Observations	4549	4549
R^2	0.8072	0.7491

This table reports the effect of mortgage complaint disclosure on mortgage applications, under three alternative definitions of a local market: a ZIP Code area, an MSA, and a state. The coefficients and corresponding t-statistics are estimated from pooled regressions of the dependent variables shown in each column header on the independent variables listed. *Mortgage Application (#)* is the log of the number of mortgage applications to a bank in a local market-year. *Mortgage Application ($)* is the log of the total dollar amount (in thousands) of mortgage applications to a bank in a local market-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a local market against a bank divided by the number of mortgage originations by the bank in the local market in 2011. *Post* is an indicator equal to one for years in and after 2013. *Approval Rate* is the mortgage approval rate of a bank in a local market in year *t*-1. *Branch Presence* is an indicator equal to one for the presence of a branch of the bank in the local market in year *t*-1. *Branch Deposits* is the log of total deposits collected by a bank's branches in a given local market in year *t*-1. Bank-year fixed effects, bank-local market fixed effects, and local market-year fixed effects are included. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table A2: Complaints as of the Disclosure Date (December 1, 2011 to March 28, 2013)

Product	Frequency
Mortgage Complaints	
Loan modification, collection, foreclosure	27,274
Loan servicing, payments, escrow account	10,691
Application, originator, mortgage broker	3,137
Settlement process and costs	1,450
Credit decision, underwriting	1,019
Other mortgage issues	1,286
Total mortgage complaints	44,857
Credit Card Complaints	
Billing-related disputes	3,376
Credit-related (credit determination, credit line, credit reporting)	2,666
APR or interest rate	1,956
Collection debt dispute, practices	1,534
Fee-related	1,458
Identity theft, fraud, embezzlement	1,233
Closing/canceling account	1,179
Other credit card issues	5,257
Total credit card complaints	18,659
Other Complaints	
Bank account or service	14,705
Consumer loan	2,351
Student loan	1,108
Total other complaints	18,164
Total Complaints	81,680

In this table, we break down mortgage complaints and credit card complaints by issue. When filing a complaint, a consumer has to choose one from a pre-set list of issues. Other complaints are broken down by product.

Table A3: Effect of Mortgage Complaint Disclosure on Mortgage Applications – Alternative Designs

Panel A: Allowing mortgage complaints to vary over time

	(1)	(2)	(3)	(4)
Dependent variable =	*Mortgage Application (#)*$_{i,c,t}$		*Mortgage Application (\$)*$_{i,c,t}$	
Mortgage Complaint$_{i,c,t}$	-0.239***	-0.140	-0.243**	-0.159
	(-2.69)	(-1.61)	(-2.49)	(-1.65)
Mortgage Complaint$_{i,c,t}$×*Post*$_t$	-0.720***		-0.637***	
	(-5.21)		(-4.96)	
Mortgage Complaint$_{i,c,t}$×*Year 0*		0.005		0.002
		(0.04)		(0.01)
Mortgage Complaint$_{i,c,t}$×*Year 1*		-1.120***		-1.047***
		(-6.32)		(-6.55)
Mortgage Complaint$_{i,c,t}$×*Year 2*		-1.076***		-0.899***
		(-6.11)		(-5.87)
Approval Rate$_{i,c,t-1}$	0.032	0.046	0.109	0.122
	(0.28)	(0.45)	(1.03)	(1.39)
Branch Presence$_{i,c,t-1}$	0.090	0.059	0.035	0.005
	(0.45)	(0.30)	(0.20)	(0.03)
Branch Deposit$_{i,c,t-1}$	0.002	0.005	0.004	0.007
	(0.12)	(0.26)	(0.25)	(0.41)
Bank-year FE	Yes	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes
Observations	30627	30627	30627	30627
R^2	0.7589	0.7742	0.6973	0.7093

Panel B: Using bank-level mortgage complaints

	(1)	(2)	(3)	(4)
Dependent variable =	*Mortgage Application (#)*$_{i,c,t}$		*Mortgage Application (\$)*$_{i,c,t}$	
Mortgage Complaint$_i$ ×*Post*$_t$	-3.520**	-6.735***	-2.960	-6.436***
	(-2.08)	(-3.58)	(-1.65)	(-3.60)
ROA$_{i,t}$	-2.238	1.598	-2.773	0.950
	(-0.79)	(0.50)	(-1.05)	(0.32)
Assets$_{i,t}$	0.189***	0.252***	0.217***	0.273***
	(3.21)	(3.17)	(3.75)	(3.55)
Equity$_{i,t}$	-2.610**	-3.946**	-3.167**	-3.056*
	(-2.19)	(-2.17)	(-2.32)	(-1.98)
Deposit$_{i,t}$	-0.127**	-0.187***	-0.149***	-0.177***
	(-2.49)	(-3.04)	(-2.97)	(-3.14)
Approval Rate$_{i,c,t-1}$	0.312**	0.278	0.519***	0.383*
	(2.41)	(0.94)	(4.52)	(1.70)
Branch Deposit$_{i,c,t-1}$	0.284***	-0.020	0.262***	-0.003
	(12.83)	(-0.76)	(13.46)	(-0.18)
Branch Presence$_{i,c,t-1}$	-2.770***	0.466	-2.579***	0.226
	(-11.21)	(1.65)	(-11.23)	(1.12)
Bank FE	Yes	No	Yes	No
Bank-county FE	No	Yes	No	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes
Observations	39263	39263	39263	39263
R^2	0.3557	0.4930	0.3227	0.4671

The table reports the effect of mortgage complaint disclosure on mortgage applications using alternative designs. Panel A reports the results using a test variable that varies over time during 2012-2015. *Mortgage Application (#)* is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Application ($)* is the log of the total dollar amount (in thousands) of mortgage applications to a bank in a county-year. *Mortgage Complaint*$_{i,c,t}$ is the number of mortgage complaints from county *c* against bank *i* as of March 28 in year *t* divided by the number of mortgage originations by the bank in the county during 2011 through year *t*-1. Note that since the disclosed mortgage complaints date back to December 1, 2011, we cannot compute *Mortgage Complaint*$_{i,c,t}$ for year 2011 and thus exclude that year from the analysis. *Post* is an indicator equal to one for years in and after 2013. *Approval Rate* is the mortgage approval rate of a bank in a county in year *t*-1. *Branch Presence* is an indicator equal to one for the presence of a branch of the bank in the county in year *t*-1. *Branch Deposits* is the log of total deposits collected by a bank's branches in a given county in year *t*-1. *Year X*'s are indicators that capture the years prior to, during, and subsequent to the year of 2013 (*Year 0* = 1 for 2013). Bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Panel B reports the results using a bank-level measure of mortgage complaints as the test variable during the original sample period of 2011-2015. *Mortgage Complaint*$_i$ is the total number of mortgage complaints against bank *i* as of the disclosure date, March 28, 2013, divided by the total number of mortgage originations by the bank in 2011. Bank fixed effects and county-year fixed effects are included in columns (1) and (3). Bank-county fixed effects and county-year fixed effects are included in columns (2) and (4). Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table A4: Sensitivity Tests

Panel A: Alternative samples

Dependent variable =	*Mortgage Application (#)*$_{i,c,t}$		
	(1) Constant sample	(2) Sample period from 2012-2014	(3) At least one complaint in a county-year
Mortgage Complaint$_{i,c}$ ×*Post*$_t$	-0.286***	-0.401***	-0.636***
	(-3.49)	(-3.53)	(-5.48)
Baseline Controls	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes
Observations	22350	24570	34440
R^2	0.8804	0.7829	0.7567

Panel B: Alternative test variables

Dependent variable =	*Mortgage Application (#)*$_{i,c,t}$		
Measure of *Mortgage Complaint*$_{i,c}$ =	(1) Log of mortgage complaints (#)	(2) Scaled by # of the 3-year average of loan originations	(3) Scaled by the amount of loan originations
Mortgage Complaint$_{i,c}$ ×*Post*$_t$	-0.096***	-0.642***	-1.227***
	(-5.69)	(-5.53)	(-5.94)
Baseline Controls	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes
Observations	39263	39263	39263
R^2	0.7525	0.7526	0.7530

Panel C: Alternative dependent variables

Dependent variable =	(1) *Market Share of Application (#)*$_{i,c,t}$	(2) *Market Share of Application (\$)*$_{i,c,t}$
Mortgage Complaint$_{i,c}$ ×*Post*$_t$	-0.021***	-0.022***
	(-2.64)	(-2.78)
Baseline Controls	Yes	Yes
Bank-year FE	Yes	Yes
Bank-county FE	Yes	Yes
County-year FE	Yes	Yes
Bank clustering	Yes	Yes
Observations	39263	39263
R^2	0.6292	0.6020

Panel D: Alternative selection criteria

Dependent variable =	*Mortgage Application (#)$_{i,c,t}$*		
	(1) # of annual mortgage originations ≥ 30	(2) # of annual mortgage originations ≥ 70	(3) # of annual mortgage originations ≥ 100
Mortgage Complaint$_{i,c}$×Post$_t$	-0.492***	-0.760***	-0.852***
	(-4.68)	(-5.91)	(-6.35)
Baseline Controls	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes
Observations	53252	31638	22638
R^2	0.7350	0.7645	0.7771

This table presents the effect of mortgage complaint disclosure on mortgage application using alternative samples, test variables, dependent variables, and selection criteria. The coefficients and corresponding t-statistics in parentheses are estimated from pooled regressions of the dependent variables shown in each column header on the independent variables listed. *Mortgage Application (#)* is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for years in and after 2013. Panel A shows the results using three alternative samples. Panel B shows the results using three alternative measures of *Mortgage Complaint*. Panel C shows the results using two alternative dependent variables. *Market Share of Application (#)* is a bank's market share of the number of mortgage applications within a county-year. *Market Share of Application ($)* is a bank's market share of the dollar amount of mortgage applications within a county-year. Panel D shows the results using three alternative cutoffs for sample selection. The baseline control variables, bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table A5: Applications to FHA-insured and VA-guaranteed Loans Only

	(1)
Dependent variable =	*Mortgage Application (#)*$_{i,c,t}$
Mortgage Complaint$_{i,c}$ ×*Post*$_t$	-0.832***
	(-3.58)
Approval Rate$_{i,c,t\text{-}1}$	0.494***
	(3.05)
Branch Deposit$_{i,c,t\text{-}1}$	-0.011
	(-0.43)
Branch Presence$_{i,c,t\text{-}1}$	0.195
	(0.79)
Bank-year FE	Yes
Bank-county FE	Yes
County-year FE	Yes
Bank clustering	Yes
Observations	39263
R^2	0.6712

This table reports the results that rule out the possibility that the adoption of the Ability-to-Repay and Qualified Mortgage Rule in 2014 drives the primary findings using applications for FHA-insured and VA-guaranteed loans, which are exempt from the rule. The coefficients and corresponding t-statistics are estimated from pooled regressions of the dependent variables shown in each column header on the independent variables listed. *Mortgage Application (#)* is the log of the number of mortgage applications for FHA-insured and VA-guaranteed loans to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for years in and after 2013. *Approval Rate* is the mortgage approval rate of a bank in a county in year *t*-1. *Branch Presence* is an indicator equal to one for the presence of a branch of the bank in the county in year *t*-1. *Branch Deposits* is the log of total deposits collected by a bank's branches in a given county in year *t*-1. Bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Table A6: Cross-Sectional Analyses Based on Information Dissemination

Panel A: Mortgage applications

Dependent variable =	*Mortgage Application (#)$_{i,c,t}$*	
	(1)	(2)
Partitioning variable =	*ΔGoogle SVI*	*Lobbying consumer groups*
Mortgage Complaint$_{i,c}$×Post$_t$	-0.566***	-0.529***
	(-4.67)	(-4.15)
Mortgage Complaint$_{i,c}$×Post$_t$×High	-0.164**	-0.272***
	(-2.39)	(-4.84)
Baseline Controls	Yes	Yes
Bank-year FE	Yes	Yes
Bank-county FE	Yes	Yes
County-year FE	Yes	Yes
Bank clustering	Yes	Yes
Observations	39263	39263
R^2	0.7526	0.7530

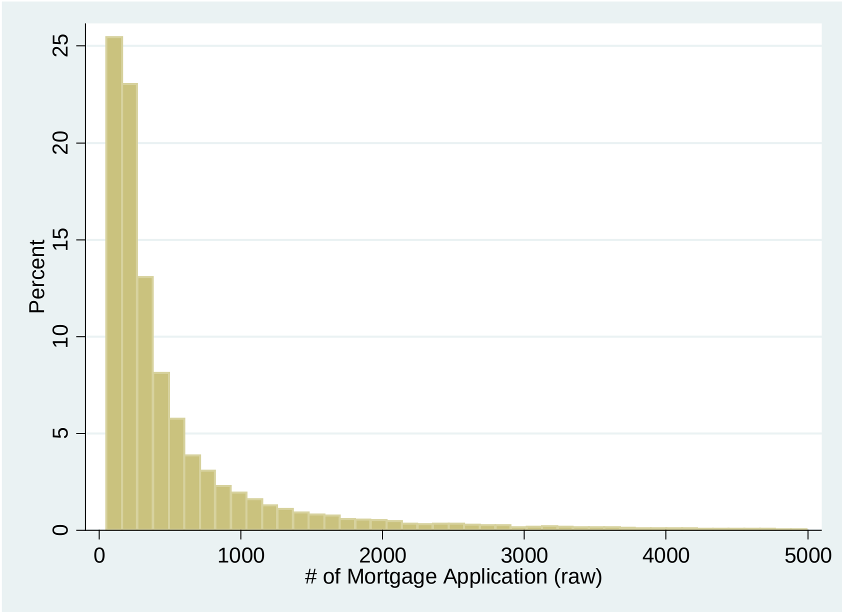
Panel B: Disciplinary effects

Dependent variable =	*Mortgage Complaint$_{i,c,m+1}$*	
	(1)	(2)
Partitioning variable =	*ΔGoogle SVI*	*Lobbying consumer groups*
Mortgage Complaint$_{i,c,m}$	0.728***	0.729***
	(16.66)	(17.22)
Mortgage Complaint$_{i,c,m}$ ×Post$_m$	-0.068***	-0.053***
	(-3.23)	(-2.78)
Mortgage Complaint$_{i,c,m}$ ×Post$_m$×High	-0.068***	-0.072***
	(-4.19)	(-7.90)
Bank clustering	Yes	Yes
Observations	36730	36730
R^2	0.1817	0.1837

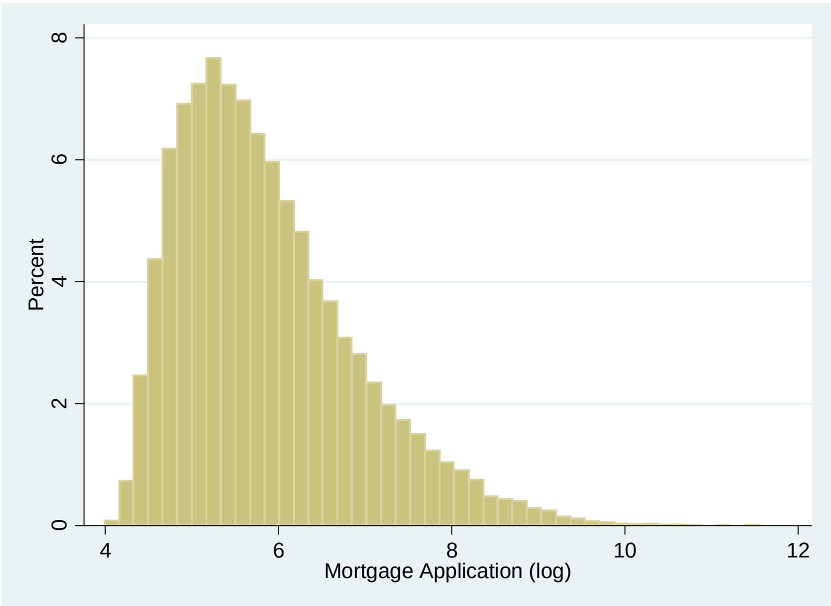
This table reports the effect of mortgage complaint disclosure on mortgage applications (in Panel A) and the rate of mean reversion of monthly mortgage complaints conditional on two partitioning variables related to the strength of information dissemination. *Mortgage Application* (#) is the log of the number of mortgage applications to a bank in a county-year. *Mortgage Complaint* is the number of mortgage complaints as of the disclosure date from a county against a bank divided by the number of mortgage originations by the bank in the county in 2011. *Post* is an indicator equal to one for mortgage application years in and after 2013. Δ*Google SVI* is the state-level change in the Google Search Volume Index for the keyword "CFPB" during 12 months before and after the release date. *Lobbying consumer groups* is the number of consumer groups that are in favor of the public complaint database as expressed in their comment letters and have a local branch in a state, scaled by the state's population in 2018. *High* is an indicator equal to one for states that have the above-median levels of Δ*Google SVI* and *Lobbying consumer groups*, respectively. In Panel A, the baseline control variables, bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Panel C presents the regression results using bad performers only conditional on two partitioning variables. The unit of analysis is at the bank-county-month level. Bad performers are banks that have the above-median level of *Mortgage Complaint$_{i,c,m}$* in each county and year. *Mortgage Complaint$_{i,c,m}$* is the number of monthly mortgage complaints against a bank in a county in month *m* scaled by the number of mortgage originations by the bank in the county in that year. *Post$_m$* is an indicator equal to one for year-months in and after March 2013. Standard errors are clustered by bank. *, **, and *** denote two-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Figure A1: Distribution of the Number of Mortgage Applications

Panel A: Number of mortgage applications (raw value)



Panel B: Log of the number of mortgage applications



This figure shows the histogram of the number of mortgage applications measured at the bank-county-year level. Panel A shows the distribution of the number of mortgage applications (raw value), whereas Panel B shows the distribution after we take the log of the raw value.