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Public Disclosure and Consumer Financial Protection

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Abstract

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 disclosures. 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.

I. Introduction

Residential mortgages are the single largest financial transaction for most households. Mortgage debt in the U.S. accounts for 52.7% of household debt (Campbell (2016)). American Community Survey and the U.S. Flow of Funds report that by the end of 2016, 48 million homeowners in the United States had a mortgage, and the total mortgage debt was $9.7 trillion. Yet, consumers often lack information about the quality of mortgage products and services. It is often difficult for consumers to learn from experience since they undertake 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

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macroeconomic and borrower circumstances (Campbell, Jackson, Madrian, and Tufano (2011)). Social taboos regarding discussing personal finances often hinder the diffusion of experiences, 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 in mortgage markets.[1]

Since 2011, the Consumer Financial Protection Bureau (CFPB) has accepted complaints about 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 to the public a complaint database, including individual complaints, their locations and submission dates, types of products and issues, and the names and responses of the banks involved. Most of the complaints in the database (55%) as of the release date are mortgage-related. 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 … to improve the transparency and efficiency of such consumer financial markets" (CFPB (2013)). Despite the importance of the stated goals, little evidence exists on its effectiveness in protecting consumers. In this article, we investigate the following questions. Does the disclosure of more mortgage complaints against a bank lead to fewer mortgage applications to it? Moreover, does such public disclosure incentivize banks to reduce mortgage complaints?

It is a priori unclear whether the release of mortgage complaints influences the decisions of consumers and banks. Critics doubt the usefulness of the database since the CFPB does not verify complaint contents, draw a random subset of the customer experience, or provide necessary context.[2] Consumers' limited search in the mortgage market (Woodward and Hall (2012), Allen, Clark, and Houde (2013)) may prevent them from incorporating the data into their decisions. Additionally, consumers may not have many alternatives if the local residential mortgage-origination market is dominated by a few banks (Stanton, Walden, and Wallace (2014)). To the extent that the mortgage complaints reveal little useful information and do not incur consumer response, banks will have few incentives to reduce consumer dissatisfaction (Fung, Weil, Graham, and Fagotto (2004)).

[1]For studies of limited learning from experience or other consumers, see Zelizer (1997) and Campbell et al. (2011). For studies of distorted recommendations from financial advisors, see Inderst and Ottaviani (2012) and Guiso, Pozzi, Tsoy, and Gambacorta (2022). For studies of consumer biases, inattention, and financial illiteracy, see DellaVigna (2009), Lusardi and Tufano (2015), and Keys, Pope, and Pope (2016). For studies of financial exploitation of consumers, see Gurun, Matvos, and Seru (2016) and literature reviews by Campbell (2006), (2016). The Consumer Financial Protection Bureau reports $13.5 billion in consumer relief for 175 million people ordered as a result of enforcement actions for violations of consumer financial protection laws through 2021 (https://www.consumerfinance.gov/enforcement/enforcement-by-the-numbers/).

[2]For example, the Consumer Mortgage Coalition (2012) 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."

On the other hand, to enhance the informativeness of the disclosures, the CFPB confirms the commercial relationship and consolidates duplicate filings before adding a complaint to the public database. Moreover, consumers do not necessarily have to use the database directly. Consumer organizations and other third parties can mine the database and help consumers make more informed decisions (CFPB (2012)).[3] As a result, mortgage applications to banks receiving more complaints should decline after the disclosures. The decline, along with other reputational costs, incentivizes banks to take actions to reduce mortgage complaints.[4]

We examine CFPB-supervised banks (those covered in the complaint data) that have mortgage applications in the Home Mortgage Disclosure Act (HMDA) database. We obtain the banks' mortgage complaints from the CFPB Consumer Complaint Database. This database was released on Mar. 28, 2013, and covers complaints dating from Dec. 1, 2011. We begin by investigating the premise that the disclosure of these complaints reveals 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 and the settlement amounts from CFPB enforcement actions over the next 5 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 and the initial reaction does not reverse over the next 6 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 from 2011 to 2015.[5] The dependent variable captures the annual county-level

[3]For example, the California Reinvestment Coalition (2018) states it "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." 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/).

[4]Banks have incentives to use the database to improve the quality of their mortgage products and services, as they often compare themselves to their 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)).

[5]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, Loutskina, and Strahan (2016), Cortes and Strahan (2017), Mian and Sufi (2017), and Aobdia, Dou, and Kim (2021)). Aggregating applications at the ZIP, the Metropolitan Statistical Area (MSA), and the state levels does not alter our inferences, as shown in Table A1 in the Supplementary Material. We also find robust results using bank-level complaints in an alternative specification and discuss weaknesses of that approach in Section IV.B.

volume of mortgage applications for each bank. The test variable is an interaction between a bank's county-level exposure to mortgage complaints (M_COMPLAINT) and an indicator equal to 1 for the years during and after the public disclosure (i.e., 2013–2015), and 0 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). We estimate regressions of the annual county-level volume of mortgage applications to a bank on its county-level exposure to mortgage complaints interacted with POST, and county-year, bank-year, and bank-county fixed effects. This specification allows us to isolate the effects of public disclosure from many confounding factors. In particular, the county-year fixed effects capture economic shocks to local credit demand (e.g., industry composition and housing prices). The bank-year fixed effects absorb bank-specific shocks (e.g., changes in capital ratios and bank liquidity) that may be correlated with both mortgage complaints and applications. The bank-county fixed effects remove time-invariant 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 III, 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 (i.e., a generalized difference-in-differences-in-differences; Gruber (1994), Pischke (2005), and 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 1-standard-deviation increase in disclosed mortgage complaints is associated with a 10.5% decrease in the number of mortgage applications and a 9.1% decrease in their dollar amount. The decrease does not occur 1 year before or during the release year, and first appears 1 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 and making mortgage complaint information publicly available helps consumers avoid lenders with low-quality products and services. We also find that the disclosure effect is more pronounced for counties with more sophisticated consumers (i.e., more high school graduates) and higher credit competition, in states with greater changes in Internet searches for the keyword "CFPB" around the disclosure and more consumer groups that file comment letters in favor of the public disclosure of consumer complaints, as well as for banks with more severe complaints.[6]

[6]Buchak, Matvos, Piskorski, and Seru (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 control for the presence and size of banks' branches as well as their mortgage approval rates in a county

We conduct three additional sets of tests to rule out alternative explanations. First, despite the difference-in-differences-in-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. Second, 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 in those areas to the target banks (Squires (2003), Dou and Zou (2019)). We find that nonmortgage 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. Third, 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.

Next, 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. Together, the results suggest that the disclosure of mortgage complaints disciplines banks to improve the consumer experience with their mortgage products and services.

We also perform several exploratory analyses to further examine this disclosure regulation. We observe that the reduction in mortgage applications does not persist in the long run, in line with banks taking actions to reduce consumer dissatisfaction. We also find consumers' reactions to complaints that likely reflect banks' wrongdoing arise less from minority applicants, consistent with less digital access for minorities. Finally, we find that changes in aggregate mortgage applications to CFPB-supervised banks and other financial institutions around the disclosure do not vary with the total mortgage complaints in a county. The results suggest a consumer migration among CFPB-supervised banks rather than a reduction in total mortgage demand for these banks.

This study contributes to the debate about 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 CFPB's acting director have proposed making the complaint database invisible to the public.[7] Our findings suggest that public disclosure of complaints facilitates

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 (2018) is less prevalent.

[7]See "Public window on financial complaints could be closing soon," July 10, 2017, *AP News*; "CFPB could hide consumer complaints from public, advocates fear," Apr. 14, 2018, *MarketWatch*.

consumer protection in mortgage markets, and eliminating this disclosure may reduce mortgage consumers' welfare.

Prior studies show that regulatory disclosure policies are effective in some settings (Jin and Leslie (2003), Rauter (2020), and Duguay, Rauter, and Samuels (2022)) but not in others (Mukamel and Mushlin (2001), Ben-Shahar and Schneider (2014)). Little is known about whether disclosing mortgage complaints advances the regulatory goals of protecting consumers. Our findings suggest that such a policy facilitates consumer financial protection. Our article also contributes to the literature on misconduct in the financial services industry (Akins, Dou, and Ng (2017), Gurun, Stoffman, and Yonker (2018), Egan, Matvos, and Seru (2019), Griffin, Kruger, and Maturana (2019), Gao, Kleiner, and Pacelli (2020), and Dou, Jagtiani, Ronen, and Maingi (2022)). We show that consumer complaint disclosure plays an active role in combating the misbehavior of financial institutions and is likely to bring a meaningful change to consumers' welfare considering the economic importance of residential mortgages.

There are two caveats to our study. First, we examine only consumer financial protection in mortgage markets and cannot speak to social welfare. When facing multitasks, banks may divert more resources away from products that are not covered in the complaint database to mortgages. Banks may also bear excess costs in the short run and benefit from consumers' increased demand in the long run due to better consumer protection. Future research is necessary to quantify the social effect of this disclosure policy. Second, our analyses are confined to local mortgage markets and thus may not be generalizable to national/global markets or other financial products.

II. Background and Related Research

A. 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. Initially, the CFPB 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 and requires a response within 15 calendar days.[8] 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 Oct. 10, 2012, the bureau added credit card complaints back to

[8]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., Mar. 28, 2013), 96.8% of complaints receive a timely response.

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Dec. 1, 2011. On Mar. 28, 2013, the database was expanded to disclose complaints about mortgages, bank accounts or services, consumer loans, and student loans. Mainstream media immediately reported that this database was available to the public.[9] In the database, mortgage complaints date back to Dec. 1, 2011, whereas complaints about the other three financial products date back to Mar. 1, 2012. Since the initial release, new complaints have been posted daily to the public database. As of the disclosure date of Mar. 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 in the Supplementary Material 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 nonmonetary) 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.[10] The database includes only complaints against banks under the supervision of the 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 nonmember banks), and thus are not included in the database.

B. Related Research

Our study relates to three strands of literature. First, finance and marketing research investigates the causes and consequences of customer reviews and

[9]For example, see "BofA tops financial-complaint list," Mar. 28, 2013, *The Wall Street Journal*; "Expert, research available: Leveraging predictive analytics to avoid CFPB complaint list," Mar. 28, 2013, *Business Wire*; "CFPB announces massive scope for complaint database," Apr. 1, 2013, *American Banker*; "Banks roused by the CFPB's database of complaints," Apr. 4, 2013, *Bloomberg Businessweek*; "The government's new mortgage complaint window is open," Apr. 5, 2013, *Daily Herald*; and "Mortgage-related complaints make up almost half of cases in federal database," Apr. 5, 2013, *The Washington Post.*

[10]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 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.

customer grievances specifically.[11] Many unique features of the CFPB Consumer Complaint Database and residential mortgage markets, as discussed in the introduction, make it difficult to extrapolate their findings 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 exploit a shock to the disclosure policy of the CFPB to isolate the effect of disclosure on consumers and banks.

Second, consumer finance studies document that biases, inattention, and cognitive limitations prevent consumers from making rational choices and explore whether more salient forms of *private* disclosures of key financial terms to consumers help them make better decisions, with mixed results.[12] We study *public* disclosure, which allows consumers to tap the wisdom of the crowd by browsing the database directly or relying on a marketplace of ideas, such as analysis of the database by third parties (e.g., consumer groups). We also 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 Consumer Complaint Database to address distinct research questions. Raval (2020) studies which demographic characteristics of a community are associated with higher complaint rates. Hayes, Jiang, and Pan (2021) investigate whether the state-level attitude of trust relates to the number of complaints and whether the establishment of the CFPB 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. None of these studies explore the consequences of disclosing the complaint database to the public. We also consider 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.

III. Data and Research Design

A. Data and Sample Construction

In Table 1, we outline the sample selection procedure. We define the unit of analysis as the bank-county-year. We first obtain mortgage applications from 2011 to 2015 from the HMDA database. Because the complaint database only covers

[11]For studies of customer reviews, see Chevalier and Mayzlin (2006), Lee, Hosanagar, and Tan (2015), Fornell, Morgeson, and Hult (2016), Huang (2018), Tang (2018), and Liu, Lee, and Srinivasan (2019)). For studies of customer grievances, see 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), and Ma, Sun, and Kekre (2015).

[12]For studies of consumer irrationality, Agarwal, Chomsisengphet, Mahoney, and Stroebel (2015), Agarwal, Rosen, and Yao (2016), Agarwal, Ben-David, and Yao (2017), and Alexandrov and Koulayev (2018). For studies of private disclosure, see Lacko and Pappalardo (2007), (2010), Stango and Zinman (2011), (2014), Navarro-Martinez, Salisbury, Lemon, Stewart, Mathews, and Harris (2011), Agarwal et al. (2015), Seira, Elizondo, and Laguna-Muggenburg (2017), and Adams, Hunt, Palmer, and Zaliauskas (2021).

TABLE 1
Sample Selection

Table 1 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.

	Bank Level		Bank-County-Year Level		Application Level
Selection Criteria	Total Obs.	Obs. with a Complaint	Total Obs.	Obs. with a Complaint	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

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, Plosser, and Vickery (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 0 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 from 2011 to 2015. Of the 39,263 bank-county-years (118 banks), 18,471 (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.

B. Research Design

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:

[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.

[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).

$$(1) \qquad Y_{i,c,t} = \alpha_{c,t} + \lambda_{i,t} + \mu_{i,c} + \beta_1 \text{M\_COMPLAINT}_{i,c} \times \text{POST}_t + \mathbf{X}_{i,c,t-1} + \varepsilon_{i,c,t},$$

where i indexes banks, c indexes counties, t indexes time, Y represents one of the two proxies for mortgage applications, α denotes the county-year fixed effects, λ denotes the bank-year fixed effects, and μ denotes the bank-county fixed effects. For the dependent variable, we take the log of the number of mortgage applications (M_APPLICATION_NUM) or their dollar amount (M_APPLICATION_DOLLAR). M_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. POST$_t$ is an indicator variable equal to 1 for year t that is in or after 2013, and 0 otherwise. The HMDA database provides the years but not the dates of mortgage applications, precluding a finer definition of POST$_t$ by the disclosure date (i.e., Mar. 28, 2013). **X** is a vector of control variables. In particular, we include the following variables: i) the fraction of mortgages approved by a bank in a county (APPRV_RATE), since higher approval rates may attract more applications (Aiello, Garmaise, and Natividad (2023)), ii) an indicator variable equal to 1 for the brick-and-mortar presence of the bank in the county-year (BRANCH_PRES), and iii) the log of total deposits collected by the bank's branches in the county-year (BRANCH_DEP). The two branch variables capture banks' local presence that reduces application costs for consumers. All three variables are lagged by 1 year to ensure that mortgage applications during the year do not affect the control variables.

Equation (1) essentially represents a triple-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 changes in loan applications around the disclosure for banks with a high number of complaints in a county (the first difference) to banks with a low number of complaints in the same county (the second difference), relative to counties in which they receive the *same* level of complaints (the third difference). For example, let us consider only two possible values of M_COMPLAINT$_{i,c}$: 1 for banks receiving a high (e.g., above-median) number of complaints in a county as of the disclosure date, and 0 otherwise. As shown in Figure 1, Wells Fargo (WFB) received a high number of complaints in McHenry County and Kendall County in Illinois, whereas Bank of America (BOA) received a high number of complaints in McHenry County but not in 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

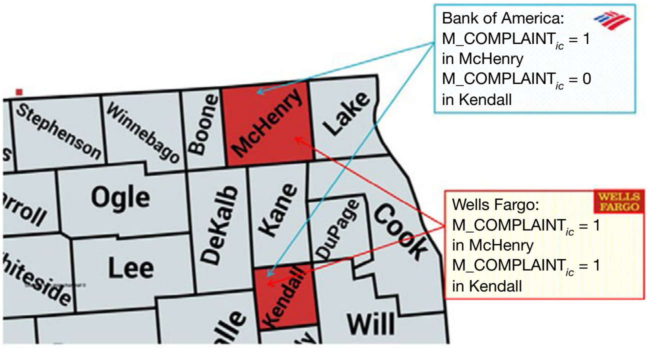
[15]In the primary analysis, we do not allow M_COMPLAINT$_{i,c}$ to vary with time to ease the interpretation of β_1 in a traditional triple-differences design. Nevertheless, our inferences are robust to updating M_COMPLAINT$_{i,c}$ by year (see Section IV.B).

[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

FIGURE 1

An Illustration of the Triple-Differences Design

Figure 1 provides an example to illustrate the triple-differences identification strategy. For expositional purposes, we assume there are only two possible values of M_COMPLAINT$_{i,c}$: 1 for banks receiving a high (above-median) number of complaints from a county as of the disclosure date, and 0 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.



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 results are stronger if clustered at the bank-year level.

C. Descriptive Statistics

In Panel A of Table 2, we report descriptive statistics for the variables used in the regression analyses. The variable definitions are 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 (= $e^{10.876}$ × 1,000), respectively. M_COMPLAINT has a mean of 0.125. The average mortgage approval rate is 71%, and an average bank has at least one branch in 58.6% of county years. Unsurprisingly, given that the CFPB supervises large banks, our sample banks have a median of \$189 billion in assets (= $e^{19.057}$ × 1,000). The mean equity and earnings are 11% and 0.9% of total assets, respectively. In the average county, 88.3% of the population has a high school diploma (EDUC = 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 mortgage complaint is stable over time and each state is well represented.

complaints at the bank-year, bank-county, and county-year levels). Our empirical model simply requires that the disclosure of local complaints (M_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).

TABLE 2

Descriptive Statistics

Panel A of Table 2 presents descriptive statistics of variables used in our analyses. M_APPLICATION_NUM is the log of the number of mortgage applications to a bank in a county year. M_APPLICATION_DOLLAR is the log of the total dollar amount (in thousands) of mortgage applications to a bank in a county year. M_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 1 for years in and after 2013. APPRV_RATE is the mortgage approval rate of a bank in a county in year $t-1$. BRANCH_PRES is an indicator equal to 1 for the presence of a branch of the bank in the county in year $t-1$. BRANCH_DEP is the log of total deposits collected by a bank's branches in a given county in year $t-1$. ASSET is the log of total assets. EQUITY is total equity divided by total assets. ROA is earnings divided by total assets. DEPOSIT is the log of total deposits. EDUC is the proportion of the population with a high school diploma in a county measured in 2012. COMPETE is $-1 \times$ the Herfindahl–Hirschman Index (HHI) of mortgage originations in a county. SEVERE 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).

Panel A. Summary Statistics (Bank-County-Year Observations)

Variable	No. o Obs.	Mean	Std. Dev.	Q1	Median	Q3
M_APPLICATION_NUM	39,263	5.873	1.030	5.100	5.673	6.446
M_APPLICATION_DOLLAR	39,263	11.064	1.200	10.186	10.876	11.761
M_COMPLAINT	39,263	0.125	0.164	0.000	0.000	0.222
POST	39,263	0.537	0.499	0.000	1.000	1.000
APPRV_RATE	39,263	0.707	0.179	0.656	0.743	0.811
BRANCH_PRES	39,263	0.586	0.493	0.000	1.000	1.000
BRANCH_DEP	39,263	7.296	6.241	0.000	10.948	12.564
ASSET	39,263	18.121	5.173	17.813	19.057	21.246
EQUITY	39,263	0.110	0.041	0.102	0.112	0.125
ROA	39,263	0.009	0.007	0.005	0.009	0.013
DEPOSIT	39,263	17.583	5.008	17.163	18.701	20.563
EDUC	39,263	0.883	0.050	0.861	0.892	0.917
COMPETE	39,263	−0.094	0.045	−0.117	−0.088	−0.063
SEVERE	39,263	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	3,827	4,809
2012	4,320	5,229
2013	4,241	4,810
2014	3,113	2,857
2015	2,970	3,087
Total	18,471	20,792

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	1,301	1,221	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	1,260
Delaware	53	41	North Dakota	26	54
Florida	1,542	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	1,152
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	18,471	20,792

IV. Results

A. Validation of Mortgage Complaint Disclosures

We begin by examining the information content of mortgage complaints. 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 ($M\_COMPLAINT_i$). The validation consists of two parts. First, we correlate three metrics with $M\_COMPLAINT_i$ to verify that this variable contains information about the quality of mortgage products and services. The first two metrics are the number of CFPB enforcement actions against a bank regarding mortgage issues and the total settlement amounts (in millions) in a 5-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 ($ENFORCEMENT_i$ and $SETTLEMENT_i$). Thirty-four banks were subject to enforcement actions and paid $3.9 billion in the settlement. The third metric is the customer satisfaction score ($SATISFACTION_i$) from Consumer Reports, a nonprofit organization known for impartiality and technical expertise in reviewing products (De Langhe, Fernbach, and Lichtenstein (2016)).[17] We are able to obtain the scores for 46 of the sample banks. Panel A of Table 3 shows that $M\_COMPLAINT_i$ is significantly positively (negatively) related to $ENFORCEMENT_i$ and $SETTLEMENT_i$ ($SATISFACTION_i$). The results reject the null that the complaints are entirely random and contain no information on the quality of mortgage products and services.

Second, we assess how much *new* 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:

$$R_t = \alpha + \beta \times R_{m,t} + \gamma \times D_t + \varepsilon_t, \tag{2}$$

where R_t denotes the portfolio returns of 60 CFPB-supervised public banks (or 320 non-CFPB-supervised public banks), $R_{m,t}$ denotes the 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: Mar. 28, 2013.

In Panel B of Table 3, we present OLS regression results of estimating equation (2). We find that the coefficient on D_t is negative and statistically significant (2-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

[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).

TABLE 3

Validation of Mortgage Complaint Disclosures

Table 3 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 is the log of one plus the number of the CFPB's enforcement actions taken against the bank over the 5 years after the disclosure date. SETTLEMENT is the log of the total amount (in millions) of the settlement from the enforcement actions. SATISFACTION is consumers' overall satisfaction score with their banks, surveyed by *Consumer Reports*, ranging from 60 to 100. M_COMPLAINT is the number of mortgage complaints against bank *i* as of the disclosure date, Mar. 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:

$$R_t = \alpha + \beta \times R_{m,t} + \gamma \times D_t + \varepsilon_t,$$

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 1 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. M_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. ASSET is the log of total assets, EQUITY is total equity divided by total assets, ROA is earnings divided by total assets, and DEPOSIT is the log of total deposits, all of which are measured at the end of 2012 for the time-series regression. Standard errors are presented in parentheses. *, **, and *** denote 2-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A. Cross-Sectional Regressions

Dependent Variable	ENFORCEMENT	SETTLEMENT	SATISFACTION
	1	2	3
M_COMPLAINT$_i$	3.853***	21.510***	−44.227***
	(3.51)	(4.75)	(−2.91)
No. of obs.	118	118	46
R^2	0.0958	0.1630	0.1611

Panel B. Market Reaction to the Disclosure Event

Dependent Variable	R_t	
	CFPB Banks	Non-CFPB Banks
	1	2
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

Dependent Variable	CAR			
	1	2	3	4
Window =	[−2, +2]	[−2, +2]	[+3, +180]	[+3, +180]
Intercept	−0.003	−0.003	0.000	0.002
	(−1.06)	(−0.20)	(0.70)	(0.79)
M_COMPLAINT$_i$	−0.006**	−0.006**	0.000	0.000
	(−1.99)	(−2.07)	(0.80)	(1.33)
ASSET		−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)
DEPOSIT		0.000		0.000
		(0.039)		(0.11)

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release date (untabulated). In contrast, we find no reaction of non-CFPB supervised banks' stock prices around the release date (2-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 (M_COMPLAINT$_i$). We control for banks' total assets (ASSET), 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. We follow Sefcik and Thompson's (1986) approach over 360 trading days surrounding the disclosure date and report portfolio time-series regression results in Panel C of Table 3. 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 over a more extended period.

The first and second columns of Panel C of Table 3 show that a bank's stock returns over the [−2, +2] window are negatively associated with the intensity of mortgage complaints filed against the bank as of the release date (2-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 more intense mortgage complaints. In sum, the results in Table 3 confirm 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]

B. Primary Results

In this subsection, we examine the real effect the public disclosure of complaint information has on consumers' mortgage application decisions. We use the log of the number and the dollar amount of mortgage applications as the dependent variables in equation (1) and report the results in separate columns of Table 4.[19] We add the three sets of fixed effects in stages and observe significantly negative coefficients on M_COMPLAINT × POST (2-tailed p-value < 0.01) throughout. The results indicate 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. The magnitude of the coefficients declines as we add more fixed effects, which are likely to strip out effects of correlated omitted variables at the corresponding levels. For example, bank-year fixed effects absorb the CFPB enforcement action variables and consumer satisfaction scores in Table 3. In columns 3 and 7, the coefficients on M_COMPLAINT × POST are −0.640 and − 0.554, with 95% confidence intervals

[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]Figure A1 in the Supplementary Material shows that taking the log of the number and the dollar amount of mortgage applications effectively reduces the skewness of the raw value.

TABLE 4

Effect of Mortgage Complaint Disclosure on Mortgage Applications

Table 4 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. M_APPLICATION_NUM is the log of the number of mortgage applications to a bank in a county year. M_APPLICATION_DOLLAR is the log of the total dollar amount (in thousands) of mortgage applications to a bank in a county year. M_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 1 for years in and after 2013. APPRV_RATE is the mortgage approval rate of a bank in a county in year $t-1$. BRANCH_PRES is an indicator equal to 1 for the presence of a branch of the bank in the county in year $t-1$. BRANCH_DEP is the log of total deposits collected by a bank's branches in a given county in year $t-1$. PRE1, POST0, POST1, and POST2 are indicators set to one for 2012, 2013, 2014, and 2015, respectively. Bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors clustered by bank are presented in parentheses. *, **, and *** denote 2-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Dependent Variable =	M_APPLICATION_NUM$_{i,c,t}$				M_APPLICATION_DOLLAR$_{i,c,t}$			
	1	2	3	4	5	6	7	8
M_COMPLAINT$_{i,c}$ × POST$_t$	−0.829***	−0.719***	−0.640***		−0.730***	−0.683***	−0.553***	
	(−7.08)	(−3.38)	(−5.51)		(−7.11)	(−3.28)	(−4.89)	
POST$_t$	−0.164***				−0.168***			
	(−5.04)				(−5.25)			
M_COMPLAINT$_{i,c}$ × PRE1				0.013				0.064
				(0.07)				(0.37)
M_COMPLAINT$_{i,c}$ × POST0				−0.066				−0.026
				(−0.37)				(−0.16)
M_COMPLAINT$_{i,c}$ × POST1				−1.042***				−0.922***
				(−5.07)				(−4.43)
M_COMPLAINT$_{i,c}$ × POST2				−1.027***				−0.819***
				(−4.76)				(−3.70)
APPRV_RATE$_{i,c,t-1}$	0.408	0.147	0.156	0.177*	0.476	0.203	0.210**	0.228***
	(1.05)	(0.78)	(1.62)	(1.92)	(1.44)	(1.05)	(2.32)	(2.70)
BRANCH_PRES$_{i,c,t-1}$	−0.057	0.010	0.017	0.018	−0.019	0.019	0.022	0.023
	(−1.63)	(0.40)	(0.87)	(0.94)	(−0.81)	(0.98)	(1.31)	(1.39)
BRANCH_DEP$_{i,c,t-1}$	0.858**	0.154	−0.029	−0.048	0.399	−0.003	−0.125	−0.142
	(2.26)	(0.60)	(−0.15)	(−0.24)	(1.50)	(−0.01)	(−0.72)	(−0.83)
Bank-county FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank-year FE	No	No	Yes	Yes	No	No	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs.	39,263	39,263	39,263	39,263	39,263	39,263	39,263	39,263
R^2	0.1991	0.4665	0.7524	0.7619	0.1768	0.4392	0.6975	0.7049

of [−0.870, −0.409] and [−0.778, −0.329], respectively. Regarding the magnitude of the effect, a 1-standard-deviation increase in M_COMPLAINT translates into a 10.5% (= 0.164 × 0.640) decrease in the number of mortgage applications after the disclosure, as well as a 9.1% (= 0.164 × 0.553) decrease in the total dollar amount of mortgage applications.[20]

An 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. To rule out this alternative explanation, we estimate the dynamic effects by interacting

[20]The magnitude of the effect is comparable to prior studies' findings. Huang (2018) estimates that a one-standard-deviation decrease in abnormal customer ratings on Amazon.com is related to a 11.1% (= 0.309 × 0.360) reduction in sales growth. Luo (2009) estimates that a one standard deviation increase in customer complaints is associated with a 14.8% $(=(1+38.586\times0.0003)^{12}-1)$ reduction in annualized idiosyncratic stock returns in the airline industry. While our article differs from these studies in several dimensions (periods, industries, measurement of reviews/complaints), a key difference is that we exploit a disclosure shock rather than simply associate customer feedback with future outcomes. By doing so, we can better isolate the effect of disclosure from that of underlying product quality.

each year indicator around the disclosure with M_COMPLAINT. The results in columns 4 and 8 of Table 4 show that the coefficients on M_COMPLAINT × PRE1 are not statistically different from 0 (2-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 (2-tailed p-value < 0.01).[21] This 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.

There are two limitations of using the current measure of the exposure to mortgage complaints, $\text{M\_COMPLAINT}_{i,c}$: i) it does not vary over time, although the CFPB updates the database on a daily basis; and ii) it does not capture the exposure at the bank level. We conduct two additional tests to evaluate the importance of these limitations. First, we replace $\text{M\_COMPLAINT}_{i,c}$ with $\text{M\_COMPLAINT}_{i,c,t}$, which is the number of mortgage complaints from county c against bank i as of Mar. 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 Dec. 1, 2011, we cannot compute $\text{M\_COMPLAINT}_{i,c,t}$ for 2011; thus we exclude that year from the analysis. As shown in Panel A of Table A3 in the Supplementary Material, $\text{M\_COMPLAINT}_{i,c,t}$ loads significantly negatively, consistent with consumers' avoidance of banks with a bad reputation in the preperiod. More importantly, $\text{M\_COMPLAINT}_{i,c,t}$ × 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 $\text{M\_COMPLAINT}_{i,c}$ with M_COMPLAINT_{i}, which is the total number of mortgage complaints against bank i as of the disclosure date, Mar. 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 continue to find a significantly negative coefficient on M_COMPLAINT_{i} × POST (as shown in Panel B of Table A3 in the Supplementary Material). However, unlike the triple-differences design, it is difficult to rule out the possibility that omitted bank-level variables drive the result. Moreover, to the extent that the quality of mortgage products varies across locations within the same bank, M_COMPLAINT_{i} contains sizable measurement errors. Thus, this result should be interpreted with caution.

C. Sensitivity Tests

We assess the sensitivity of our findings to the initial research design choices. The results are in Table A4 in the Supplementary Material. First, we show that our

[21]We attribute this lack of reaction in the release year (2013) to two primary factors. 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.

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

inference remains the same after employing three alternative samples: A "constant sample" of bank counties that persist through the entire sample period, a sample of a shorter window around the disclosure (2012–2014), and a sample from counties with at least one complaint in a given year to ensure at least one bank with a mortgage complaint in that county-year. Second, our results are robust to using three alternative measures of banks' exposure to mortgage complaints: the log of mortgage complaints, the number of mortgage complaints scaled by the 3-year average of loan originations in 2011–2013, and the number of mortgage complaints scaled by the dollar amount of originated loans. Third, the inferences remain intact if 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. Fourth, the results are resilient 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]

D. 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 ($\text{SBL\_NUM}_{i,c,t}$) based on banks' Community Reinvestment Act reports, which have been used frequently in the small business lending literature (Dou (2021)). Using $\text{SBL\_NUM}_{i,c,t}$ as a new dependent variable, we find an insignificant coefficient on M_COMPLAINT × POST in column 1 in Table 5.

Another confounding event is that independent of the disclosure, in 2013 local community groups may have waged campaigns against banks with bad reputations, which likely received more consumer complaints (about not only mortgages but other financial products). The campaigns can provoke customer boycotts, resulting in fewer mortgage applications from those areas to the target banks (California Reinvestment Committee (2001), Squires (2003), and Dou and Zou (2019)). To rule out this explanation, we explore nonmortgage complaints from the same database. To the extent that the operations of mortgage and nonmortgage segments within a bank are correlated, nonmortgage 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 M_COMPLAINT, and then interacted with the post indicator.

[23]Defusco, Johnson, and Mondragon (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 jumbo mortgages. 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 these loans as an alternative dependent variable and continue to find robust results (see Table A5 in the Supplementary Material).

TABLE 5
Placebo Tests

Table 5 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, SBL_NUM is the log of the number of small business loans originated by a bank in a county year. In column 2, M_APPLICATION_NUM is the log of the number of mortgage applications to a bank in a county year. M_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. CC_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 1 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 clustered by bank are presented in parentheses. *, **, and *** denote 2-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Dependent Variable	$\text{SBL\_NUM}_{i,c,t}$	$\text{M\_APPLICATION\_NUM}_{i,c,t}$
	1	2
$\text{M\_COMPLAINT}_{i,c} \times \text{POST}_t$	0.068	−0.599***
	(0.75)	(−4.63)
$\text{CC\_COMPLAINT}_{i,c} \times \text{POST}_t$		0.018
		(0.18)
$\text{OTHER\_COMPLAINT}_{i,c} \times \text{POST}_t$		−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
No. of obs.	39,263	39,263
R^2	0.5268	0.7525

We add the two new interaction terms to equation (1) and reestimate the equation. Column 2 in Table 5 reports that M_COMPLAINT × POST loads significantly negatively after we control for the release of complaints about credit cards and other products. In contrast, the coefficients on CC_COMPLAINT × POST and OTHER_COMPLAINT × POST are statistically insignificant. Thus, the results suggest that the disclosure of mortgage complaints as opposed to broader types of complaints influences mortgage application decisions. The result weakens the alternative explanation that banks' local reputation combined with community activism drives the findings.

E. Matched-Pair Design

Banks with distinct characteristics (e.g., size) may respond differently to common local shocks. As such, a potential concern is that our results might be driven by the different responses to common local events other than the complaint disclosures. To mitigate this concern, we construct a matched sample based on each one of observable bank characteristics: banks' total assets (ASSET), 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, as reported in Panel A of Table 6. We reestimate equation (1) augmented with pair fixed effects using each matched sample and

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TABLE 6
Matched-Pair Design

Table 6 presents the effect of mortgage complaint disclosure on mortgage applications using four matched samples of bank-county-years with and without complaints based on ASSET, 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, M_APPLICATION_NUM is the log of the number of mortgage applications to a bank in a county year. M_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 1 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, county-year, and pair fixed effects are included. Standard errors clustered by bank are presented in parentheses. *, **, and *** denote 2-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A. Matched Sample Characteristics

	Obs. With a Complaint Mean	Obs. Without Complaint Mean	Differences 1–2	*t*-Stats.
	1	2	3	4
ASSET	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	$M\_APPLICATION\_NUM_{i,c,t}$			
Matched on	ASSET	EQUITY	ROA	DEPOSIT
	1	2	3	4
$M\_COMPLAINT_{i,c} \times POST_t$	−0.243***	−0.383***	−0.803***	−0.243***
	(−2.67)	(−3.29)	(−4.09)	(−3.26)
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
Pair FE	Yes	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes
No. of obs.	11,736	7,394	5,968	8,554
R^2	0.8582	0.8109	0.7784	0.8551

report the results in Panel B, where each column presents the result using a matched sample based on the variable indicated in the column header. We find that M_COMPLAINT × POST loads significantly negatively across all specifications. Thus, our findings cannot be attributed to differential responses to local market shocks arising from diverse bank characteristics.

F. Cross-Sectional Tests

We next perform a number of cross-sectional tests based on the characteristics of consumers, local markets, and complaints. First, 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)). We employ a county-level proxy for consumer sophistication, the proportion of the population with a high school diploma (EDUC), and define HIGH as an indicator equal to 1 for the observations that have above-median values of this variable, and 0 otherwise. We then interact it with M_COMPLAINT × POST. Column 1 in Table 7 shows that M_COMPLAINT × POST × HIGH loads significantly negatively (2-tailed *p*-value <0.01). This result suggests that greater sophistication helps customers

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TABLE 7

Cross-Sectional Analyses

Table 7 reports the effect of mortgage complaint disclosure on mortgage applications conditional on three partitioning variables. M_APPLICATION_NUM is the log of the number of mortgage applications to a bank in a county year. M_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 1 for mortgage application years in and after 2013. EDUC is the proportion of the population with a high school diploma in a county measured in 2012. COMPETE is −1 × the Herfindahl–Hirschman Index (HHI) of mortgage originations in a county. SEVERE is the fraction of mortgage complaints tagged with relief or consumer dispute. HIGH is an indicator equal to 1 for counties that have the above-median levels of EDUC and COMPETE, respectively, and for banks that have the above-median level of SEVERE. The baseline control variables, bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors clustered by bank are presented in parentheses. *, **, and *** denote 2-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Dependent Variable	M_APPLICATION_NUM$_{i,c,t}$		
Partitioning Variable	EDUC$_c$	COMPETE$_c$	SEVERE$_i$
	1	2	3
M_COMPLAINT$_{i,c}$ × POST$_t$	−0.487***	−0.473***	−0.295*
	(−3.29)	(−3.63)	(−1.92)
M_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
No. of obs.	39,263	39,263	39,263
R^2	0.7527	0.7542	0.7535

better understand and detect instances of unfair practices in the database, leading to a greater reduction in subsequent loan applications for banks with more mortgage complaints.[24]

Second, we examine whether consumers' response to mortgage complaints varies with within-county credit competition. 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 (COMPETE). We set the indicator HIGH to 1 for the observations that have above-median values of this variable, and 0 otherwise, and then interact it with M_COMPLAINT × POST. Column 2 in Table 7 shows that high credit competition strengthens consumers' response, as M_COMPLAINT × POST × HIGH loads significantly negatively (2-tailed p-value < 0.01).

Third, we examine whether consumers' reactions vary with complaint severity. To measure severity, we combine two attributes available in the complaint database: whether the bank provides monetary or nonmonetary relief and whether

[24]The results are inconsistent with the notion that sophisticated consumers know the quality of mortgage products better than others before the complaint disclosure and thus are less affected by the disclosure event. This is likely due to limited information on product quality in mortgage markets in the first place as discussed at the beginning of this article. We also create an indicator equal to one for counties with an above-median proportion of the population with a college degree (HIGH_COLLEGE) and add M_COMPLAINT × POST × HIGH_COLLEGE to the regression. We find that M_COMPLAINT × POST × HIGH continues to load significantly negatively, whereas the coefficient on M_COMPLAINT × POST × HIGH_COLLEGE is negative but statistically insignificant. The results suggest that after high school graduation, obtaining a college degree does not help consumers better incorporate the complaint data into their applications.

the consumer disputes the bank's response. Complaints closed with relief or consumer dispute are likely to be more severe than those closed with just explanations or without dispute. In Appendix C, we provide two examples and conduct textual analysis to validate this claim. We compute the fraction of complaints tagged with relief or dispute for each bank (SEVERE), set the indicator HIGH to 1 for the observations that have above-median values of this variable, and 0 otherwise, and interact it with M_COMPLAINT × POST. Column 3 in Table 7 shows that M_COMPLAINT × POST × HIGH loads significantly negatively (2-tailed p-value < 0.05), suggesting a greater consumer reaction to more severe complaints.[25]

Finally, we consider how the complaint information is disseminated and incorporated into consumers' decisions. Doing so is difficult due to the lack of available data on consumers' behavior before their mortgage applications. 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 (ΔGOOGLE_SVI) and set the indicator HIGH to 1 for the observations in states that have above-median values of ΔGOOGLE_SVI, and 0 otherwise.[26] 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.[27] 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 II.C). 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 (CONSUMER_LOBBY). The indicator HIGH is set to 1 for the observations in states that have above-median values of this variable, and 0 otherwise. Table A6 in the Supplementary Material shows that M_COMPLAINT × POST × HIGH loads significantly negatively for both partitioning variables (ΔGOOGLE_SVI and CONSUMER_LOBBY). The results suggest that consumers' Internet searches and consumer groups help disseminate the complaint information.

V. Tests for the Disciplinary Effect

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

[25]For EDUC and COMPETE, the main effect of HIGH and the interaction effect of HIGH × POST are absorbed by county-year fixed effects. For SEVERE, the main effect of HIGH and the interaction effect of HIGH × POST are absorbed by bank-year fixed effects.

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

[27]The inquiry was viewed as a precursor to restricting the public view of the complaint database (see "Consumer bureau looks to end public view of complaints database," Apr. 25, 2018, *The New York Times*).

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complaints after the public disclosure. We do not examine the number of complaints around the disclosure; naturally, banks with poorer quality products 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.[28] We construct a sample of bank-county-month observations, keep bank counties that exist both before and after the disclosure, and estimate the following regression:

$$\text{(3)}\quad \text{M\_COMPLAINT}_{i,c,m+1} = \alpha + \beta_0 \text{M\_COMPLAINT}_{i,c,m} + \beta_1 \text{M\_COMPLAINT}_{i,c,m} \times \text{POST}_m + \varepsilon_{i,c,m},$$

where $\text{M\_COMPLAINT}_{i,c,m}$ 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 consumer migration. If we use the number of loan originations in 2011 and find faster mean reversion in M_COMPLAINT after the disclosure, the results might be explained by fewer applications to banks with more complaints. POST_m is set to 1 for months in and after Mar. 2013, and 0 otherwise.

Panel A of Table 8 provides descriptive statistics for the variables used in the analyses, and Panel B presents the regression results. In the first column, the positive coefficient on M_COMPLAINT captures the natural mean revision before the public disclosure, with 0 (1) being perfect (no) mean reversion. M_COMPLAINT × POST loads significantly negatively (2-tailed p-value < 0.01). This result indicates that banks exhibit faster mean reversion in the number of mortgage complaints after the release of the database. Since the CFPB's supervision takes place at the beginning of the preperiod, it is unlikely to drive the accelerated mean reversion after the disclosure. Note that when the CFPB first launched the complaint database with only complaints about credit cards on June 19, 2012, the bureau did not specify which products would be subsequently added at which time nor did it request public comments on these issues.[29] As such, banks are unlikely to take corrective actions in anticipation of the disclosure of mortgage complaints. Nevertheless, to assess this anticipation effect, we estimate equation (3) using the predisclosure period only (i.e., up to Mar. 2013) and replace POST with an indicator for the period after June 2012 (POST_CC). Table A7 in the Supplementary Material shows that

[28]We focus on monthly mortgage complaints in order to balance two competing considerations: i) there is no sufficiently long time series to estimate the natural mean reversion in the preperiod for annual or quarterly complaints and ii) a discernible improvement in customer experience is likely to take more than a week.

[29]In its policy statement on June 15, 2012: "The Bureau notes that any extension of the disclosure system for other complaint data would not be finalized until the Bureau is able to consider whatever adjustments might be necessary in light of operational experience and to address comments received in response to this Concurrent Notice. In addition, any such extension might be phased in at different times for different products" (CFPB (2012)). Several trade associations also complained that: "each time the Bureau intends to add complaints to the public database about a certain type of consumer financial product or service, it should provide the opportunity to comment prior to doing so" (CFPB (2013), see also the Center for Capital Markets Competitiveness (2012)).

TABLE 8

Disciplinary Effects

Panel A of Table 8 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. $M\_COMPLAINT_{i,c,m}$ 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 1 for year-months in and after Mar. 2013. $HIGH_{i,c,m}$ ($LOW_{i,c,m}$) is an indicator equal to 1 for banks that have the above-median (below-median) level of $M\_COMPLAINT_{i,c,m}$ in each county and year. Standard errors clustered by bank are presented in parentheses. *, **, and *** denote 2-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A. Descriptive Statistics

Variable	No. of Obs.	Mean	Std. Dev.	Q1	Median	Q3
$M\_COMPLAINT_{i,c,m}$	70,239	0.115	0.105	0.000	0.121	0.191
$M\_COMPLAINT_{i,c,m+1}$	70,239	0.110	0.108	0.000	0.115	0.191
$HIGH_{i,c,m}$	70,239	0.506	0.500	0.000	1.000	1.000
$LOW_{i,c,m}$	70,239	0.494	0.500	0.000	0.000	1.000
$POST_m$	70,239	0.637	0.481	0.000	1.000	1.000

Panel B. Regression Analyses

	$M\_COMPLAINT_{i,c,m+1}$	$M\_COMPLAINT_{i,c,m+1}$
	1	2
$M\_COMPLAINT_{i,c,m}$	0.438*** (7.36)	
$M\_COMPLAINT_{i,c,m} \times HIGH_{i,c,m}$		0.440*** (7.17)
$M\_COMPLAINT_{i,c,m} \times LOW_{i,c,m}$		0.435*** (12.70)
$M\_COMPLAINT_{i,c,m} \times POST_m$	−0.068** (−2.60)	
$M\_COMPLAINT_{i,c,m} \times POST_m \times HIGH_{i,c,m}$		−0.072** (−2.58)
$M\_COMPLAINT_{i,c,m} \times POST_m \times LOW_{i,c,m}$		−0.023 (−1.33)
Bank clustering	Yes	Yes
No. of obs.	70,239	70,239
R^2	0.1482	0.1484

M_COMPLAINT × POST_CC does not load significantly, indicating no anticipatory actions by banks after June 2012.

To further understand the faster mean reversion after the disclosure, we create two indicators: HIGH (LOW) is set to 1 for observations with the number of complaints above (below) the median value in a county year, and 0 otherwise. These two indicators are then interacted with M_COMPLAINT and M_COMPLAINT × POST, respectively. Column 2 in Panel B of Table 8 shows that M_COMPLAINT × HIGH and M_COMPLAINT × LOW load significantly positively. Thus, before the disclosure event, both groups of banks exhibit a natural mean reversion process. More importantly, we observe a significantly negative (an insignificant) coefficient on M_COMPLAINT × POST × HIGH (M_COMPLAINT × POST × LOW). The results suggest that the disciplinary effect is concentrated among bad performers.[30]

[30]The coefficients on M_COMPLAINT × HIGH and M_COMPLAINT × LOW are statistically indistinguishable (2-tailed *p*-value = 0.75), suggesting similar mean reversion between bad and good performers before the disclosure. However, the sum of the coefficients on M_COMPLAINT × HIGH and M_COMPLAINT × POST × HIGH is significantly lower than the sum of the coefficients on M_COMPLAINT × LOW and M_COMPLAINT × POST × LOW (2-tailed *p*-value < 0.01), indicating faster mean-reversion for bad performers after the disclosure. We do not include the three sets of fixed

VI. Additional Analyses

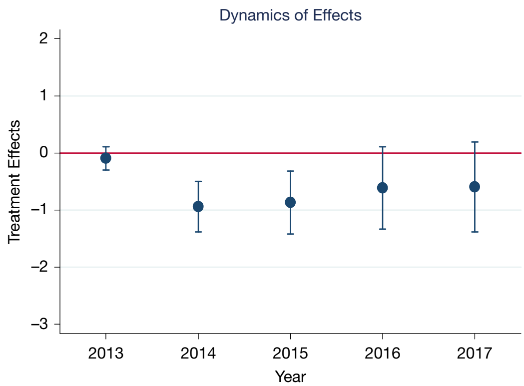
To further investigate this disclosure regulation, we perform three sets of exploratory analyses. First, to examine the effect on mortgage applications over a longer period, we extend our sample to 2017, interact M_COMPLAINT with an indicator for each year from 2013 to 2017, and replace M_COMPLAINT × POST with these interaction terms in equation (1), which makes 2012 the benchmark period. The estimated coefficient on each interaction and its 2-tailed 90% confidence interval are plotted in Graph A (Graph B) of Figure 2 for the number (dollar amount) of mortgage applications. The effect of complaint disclosure on mortgage

FIGURE 2

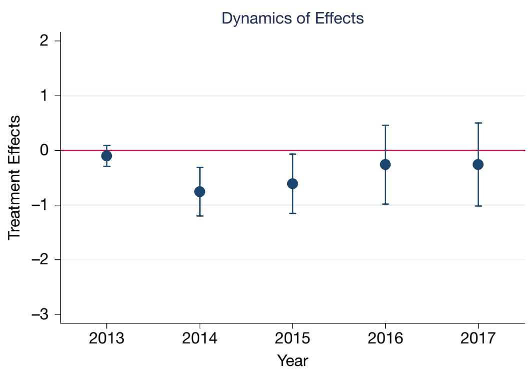
Long-Term Effects on Mortgage Applications

Figure 2 shows ordinary least squares (OLS) regression coefficients on five interaction terms and 2-tailed 90% confidence intervals based on standard errors clustered on bank. We extend our sample to 2017 (i.e., 2012–2017), interact M_COMPLAINT with an indicator for each year from 2013 to 2017, and replace M_COMPLAINT × POST with these interaction terms in equation (1), which makes 2012 the benchmark period. M_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. Graph A is for M_APPLICATION_NUM, the log of the number of mortgage applications to a bank in a county year. Graph B is for M_APPLICATION_DOLLAR, the log of the total dollar amount (in thousands) of mortgage applications to a bank in a county year.

Graph A. The Effects on M_APPLICATION_NUM



Graph B. The Effects on M_APPLICATION_DOLLAR



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applications diminishes in 2016–2017, in line with banks taking actions to reduce consumer dissatisfaction.

Second, we examine complaints that likely reflect banks' wrongdoing (e.g., fraudulent and discriminatory behavior). As complaint narratives in the database were not available until June 2015, we identify severe mortgage complaints as those closed with relief or consumer dispute (see Section IV.F and Appendix C). We then scale the number of these complaints as of the disclosure date from a county against a bank by the number of mortgage originations by the bank in the county in 2011 (M_COMPLAINT_SEV) and replace M_COMPLAINT with this variable in equation (1). We reestimate equation (1) using two subsamples where wrongdoing is more likely to occur: i) observations from banks subject to CFPB enforcement actions about mortgages and ii) those from counties with an above-median proportion of the population in low- to moderate-income areas, where the incidence of misselling, fraud, and poor customer service by banks is higher (Begley and Purnanandam (2021)). The first column of Panels A and B of Table 9 shows M_COMPLAINT_SEV × POST loads significantly negatively in both subsamples, suggesting a greater reduction in mortgage applications to banks facing more severe complaints after the disclosure. The rest of the columns report the results after splitting mortgage applications by gender and race. We find that the application reduction is statistically indistinguishable between female and male applicants (2-tailed p-value > 0.1) but significantly greater for white applicants than minorities (2-tailed p-value < 0.01), consistent with the well-documented racial disparity in accessing digital information (Atske and Perrin (2021), Martin (2021)).

Finally, we examine the effect of complaint disclosure on aggregate mortgage applications using a panel with county-year as the unit of observation. The dependent variables are the log of the number of mortgage applications to CFPB-supervised banks ($\text{M\_APPLICATION\_CFPB\_BANK}_{c,t}$) and other financial institutions ($\text{M\_APPLICATION\_OTHER}_{c,t}$) in county c and year t. The test variable is the interaction between the total number of mortgage complaints from county c as of the disclosure date divided by the number of mortgage originations by CFPB-supervised banks in 2011 (M_COMPLAINT_c) and the POST_t indicator set to one for 2013–2015. We also include the county and year fixed effects and cluster the standard error on county and year. As shown in Panel C of Table 9, $\text{M\_COMPLAINT}_c \times \text{POST}_t$ does not load for either dependent variable. The results, combined with our primary findings, suggest a consumer migration among CFPB-supervised banks rather than reduced total mortgage demand after the disclosure.

VII. Conclusion

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

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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, adding these fixed effects does not alter our inferences.

TABLE 9

Additional Analyses

Panel A (B) of Table 9 reports the effect of severe mortgage complaint disclosure on mortgage applications using observations from banks subject to CFPB enforcement actions about mortgages (counties with an above-median proportion of the population in low- to moderate-income tracts). M_COMPLAINT_SEV is the number of complaints closed with relief or consumer dispute as of the disclosure date from a county against a bank by the number of mortgage originations by the bank in the county in 2011. POST is an indicator equal to 1 for years in and after 2013. M_APPLICATION_NUM is the log of the number of mortgage applications to a bank in a county year. M_APPLICATION_FEM (M_APPLICATION_MAL) is the log of the number of mortgage applications from female (male) applicants to a bank in a county year. M_APPLICATION_NW (M_APPLICATION_W) is the log of the number of mortgage applications from nonwhite (white) applicants to a bank in a county year. The baseline control variables, bank-year fixed effects, bank-county fixed effects, and county-year fixed effects are included. Standard errors clustered by bank are presented in parentheses. Panel C reports the effect of complaint disclosure on aggregate mortgage applications using a panel with country-year as the unit of observation. M_APPLICATION_CFPB_BANK (M_APPLICATION_OHTER) is the log of the number of mortgage applications to CFPB-supervised banks (other financial institutions) in a county year. M_COMPLAINT$_c$ is the number of mortgage complaints as of the disclosure date from county *c* divided by the number of mortgage originations by CFPB-supervised banks. County and year-fixed effects are included. Standard errors clustered by county and year are presented in parentheses. *, **, and *** denote 2-tailed statistical significance at 10%, 5%, and 1% levels, respectively.

Dependent Variables	M_APPLICATION_NUM$_{i,c,t}$	M_APPLICATION_FEM$_{i,c,t}$	M_APPLICATION_MAL$_{i,c,t}$	M_APPLICATION_NW$_{i,c,t}$	M_APPLICATION_W$_{i,c,t}$
	1	2	3	4	5
Panel A. Banks Subject to CFPB Enforcement Actions About Mortgages					
M_COMPLAINT_SEV$_{i,c}$ × POST$_t$	−0.713***	−0.772***	−0.705***	−0.541**	−0.849***
	(−3.93)	(−5.56)	(−3.48)	(−2.26)	(−5.60)
Baseline controls	Yes	Yes	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes	Yes
No. of obs.	20,220	20,220	20,220	20,220	20,220
R^2	0.7916	0.7679	0.7839	0.6587	0.8049
Panel B. Counties with an Above-Median Proportion of the Population in Low- to Moderate-Income Tracts					
M_COMPLAINT_SEV$_{i,c}$ × POST$_t$	−0.700***	−0.771***	−0.687***	−0.559***	−0.826***
	(−4.44)	(−5.33)	(−4.02)	(−3.04)	(−5.44)
Baseline controls	Yes	Yes	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes	Yes
Bank clustering	Yes	Yes	Yes	Yes	Yes
No. of obs.	18,226	18,226	18,226	18,226	18,226
R^2	0.7287	0.6954	0.7208	0.5985	0.7468

Panel C. Aggregate Mortgage Applications and Complaints at the County-Year Level

	M_APPLICATION_CFPB_BANK$_{c,t}$	M_APPLICATION_OTHER$_{c,t}$
	1	2
M_COMPLAINT$_c$ × POST$_t$	0.205	−0.075
	(1.07)	(−0.81)
County FE	Yes	Yes
Year FE	Yes	Yes
Cluster by	County, Year	County, Year
No. of obs.	10,700	10,700
R^2	0.9812	0.9911

design. Specifically, we compare changes in loan applications around the disclosure for banks with a high number of complaints in a county to banks with a low number of complaints in the same county, relative to counties in which they receive the *same* level of complaints. We find a greater reduction in mortgage applications from 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'

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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.

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 M_COMPLAINT$_{i,c}$: 1 for banks receiving a high (e.g., above-median) number of complaints from a county as of the disclosure date, and 0 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:

(A-1) $$Y_{i,c,t} = \alpha_{c,t} + \lambda_{i,t} + \mu_{i,c} + \beta_1 \text{M\_COMPLAINT}_{i,c} \times \text{POST}_t + \varepsilon_{i,c,t}.$$

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

(A-2) $$E[Y_{i,c,t}|i = \text{WFB}, c = \text{Kendall}, t = 2013] - E[Y_{i,c,t}|i = \text{WFB}, c = \text{Kendall}, t = 2012] \\ = (\alpha_{\text{Kendall, 2013}} - \alpha_{\text{Kendall, 2012}}) + (\lambda_{\text{WFB, 2013}} - \lambda_{\text{WFB, 2012}}) + \beta_1.$$

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

(A-3) $$E[Y_{i,c,t}|i = \text{BOA}, c = \text{Kendall}, t = 2013] - E[Y_{i,c,t}|i = \text{BOA}, c = \text{Kendall}, t = 2012] \\ = (\alpha_{\text{Kendall, 2013}} - \alpha_{\text{Kendall, 2012}}) + (\lambda_{\text{BOA, 2013}} - \lambda_{\text{BOA, 2012}}).$$

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

(A-4) $$E[Y_{i,c,t}|i = \text{WFB}, c = \text{McHenry}, t = 2013] - E[Y_{i,c,t}|i = \text{WFB}, c = \text{McHenry}, t = 2012] \\ = (\alpha_{\text{McHenry, 2013}} - \alpha_{\text{McHenry, 2012}}) + (\lambda_{\text{WFB, 2013}} - \lambda_{\text{WFB, 2012}}) + \beta_1.$$

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

$$\text{(A-5)} \quad E[Y_{i,c,t}|i=\text{BOA}, c=\text{McHenry}, t=2013] - E[Y_{i,c,t}|i=\text{BOA}, c=\text{McHenry}, t=2012] = (\alpha_{\text{McHenry, 2013}} - \alpha_{\text{McHenry, 2012}}) + (\lambda_{\text{BOA, 2013}} - \lambda_{\text{BOA, 2012}}) + \beta_1.$$

Each of the four equations above (i.e., (A-2)–(A-5)) represents the first difference. The second difference (i.e., difference-in-differences) becomes:

$$\text{(A-2)} - \text{(A-3)} = (\lambda_{\text{WFB, 2013}} \text{-} \lambda_{\text{WFB, 2012}}) - (\lambda_{\text{BOA, 2013}} \text{-} \lambda_{\text{BOA, 2012}}) + \beta_1, \text{ and}$$
$$\text{(A-4)} - \text{(A-5)} = (\lambda_{\text{WFB, 2013}} \text{-} \lambda_{\text{WFB, 2012}}) - (\lambda_{\text{BOA, 2013}} \text{-} \lambda_{\text{BOA, 2012}}).$$

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

$$\text{(A-6)} \quad [\text{(A-2)} - \text{(A-3)}] - [\text{(A-4)} - \text{(A-5)}] = \beta_1.$$

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 approach can uncover β_1 without such an assumption.

Appendix B. Variable Definitions

M_APPLICATION_NUM$_{i,c,t}$: Log of the number of mortgage applications to bank i in county c and year t. Source: HMDA database.

M_APPLICATION_DOLLAR$_{i,c,t}$: Log of the total dollar amount (in thousands) of mortgage applications to bank i in county c and year t. Source: HMDA database.

M_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. Source: CFPB Complaint/HMDA database.

M_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. Source: CFPB Complaint/HMDA database.

POST$_t$: An indicator equal to 1 for years in and after 2013, and 0 otherwise. Source: HMDA database.

APPRV_RATE$_{i,c,t-1}$: The fraction of mortgage applications to bank i in county c that are approved in year $t-1$. Source: HMDA database.

BRANCH_PRES$_{i,c,t-1}$: An indicator equal to 1 for the presence of a branch of bank i in county c and year $t-1$, and 0 otherwise. Source: FDIC Summary of Deposits.

BRANCH_DEP$_{i,c,t-1}$: Log of total deposits collected by bank i's branches in county c and year $t-1$, and 0 otherwise. Source: FDIC Summary of Deposits.

ASSET$_{i,t}$: Log of total assets (RCFD2170 for commercial banks or BHCK2170 for bank holding companies) for bank i by the end of year t. Source: 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. Source: Y-9C/ Call Reports.

$\mathrm{ROA}_{i,t}$: Net income divided by total assets (RIAD4300/RCFD2170 for commercial banks or BHCK4300/BHCK2170 for bank holding companies) for bank i in year t. Source: Y-9C/ Call Reports.

$\mathrm{DEPOSIT}_{i,t}$: Log of total deposits (RCON2200 for commercial banks or BHDM6631 + BHDM6636 for bank holding companies) for bank i by the end of year t. Source: Y-9C/Call Reports.

EDUC_c: The proportion of the population with a high school diploma in county c measured in 2012. Source: 2012 American Community Survey.

$\mathrm{COMPETE}_c$: $-1 \times$ 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. Source: HMDA database.

SEVERE_i: The fraction of mortgage complaints tagged with relief or consumer dispute against bank i. Source: CFPB Complaint database.

$\mathrm{M\_COMPLAINT}_{i,c,m}$: 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. Source: CFPB Complaint/HMDA database.

POST_m: An indicator equal to 1 for months in and after Mar. 2013, and 0 otherwise. Source: CFPB Complaint database.

Appendix C. Validation of the Complaint Severity Measure

In Appendix C, 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 nonmonetary 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. A total of 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/lough ranmcdonald-master-dictionary/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

Relief/dispute	Words	Personal	Quant	Constrain	Litigious	Negative	Tone
	1	2	3	4	5	6	7
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
Subproduct	Conventional adjustable mortgage (ARM)
Issue	Loan modification, collection, foreclosure
Consumer consent to publish narrative	Consent provided
Consumer complaint narrative 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)."	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 {$1,400.00} plus a MIP of {$390.00} or {$1,800.00} per month with an interest rate of 2.5%. By the end of the fifth year payments blew up to {$2,800.00} plus {$390.00} of MIP to {$3,200.00} per month. Just the 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 cannot 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 reapplied 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

(continued on next page)

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EXHIBIT C2 (continued)

Two Examples of Consumer Complaint Narratives in 2015

	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 {$100,000.00} which Bank of America provided even though our home did not 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 {$110,000.00} 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 nonmonetary 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
Subproduct	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

Supplementary Material

To view supplementary material for this article, please visit http://doi.org/10.1017/S0022109023000613.

References

Adams, P.; S. Hunt; C. Palmer; and R. Zaliauskas. "Testing the Effectiveness of Consumer Financial Disclosure: Experimental Evidence from Savings Accounts." *Journal of Financial Economics*, 141 (2021), 122–147.

Agarwal, S.; I. Ben-David; and V. Yao. "Systematic Mistakes in the Mortgage Market and Lack of Financial Sophistication." *Journal of Financial Economics*, 123 (2017), 42–58.

Agarwal, S.; S. Chomsisengphet; N. Mahoney; and J. Stroebel. "Regulating Consumer Financial Products: Evidence from Credit Cards." *Quarterly Journal of Economics*, 130 (2015), 111–164.

Agarwal, S.; R. Rosen; and V. Yao. "Why Do Borrowers Make Mortgage Refinancing Mistakes?" *Management Science*, 62 (2016), 3494–3509.

Aiello, D.; M. Garmaise; and G. Natividad. "Competing for Deal Flow in Local Mortgage Markets." *Review of Corporate Finance Studies*, 12 (2023), 366–401.

Akins, B.; Y. Dou; and J. Ng. "Corruption in Bank Lending: The Role of Timely Loan Loss Recognition." *Journal of Accounting and Economics*, 63 (2017), 454–478.

Alexandrov, A., and S. Koulayev. "No Shopping in the U.S. Mortgage Market: Direct and Strategic Effects of Providing Information." CFPB Office of Research Working Paper No. 2017-01 (2018).

Allen, J.; R. Clark; and J. Houde. "The Effect of Mergers in Search Markets: Evidence from the Canadian Mortgage Industry." *American Economic Review*, 104 (2013), 3365–3396.

Angrist, J., and J. Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton, NJ: Princeton University Press (2009).

Aobdia, D.; Y. Dou; and J. Kim. "Public Audit Oversight and the Originate-to-Distribute Model." *Journal of Accounting and Economics*, 72 (2021), 1014–1020.

Atske, S., and A. Perrin. *Home Broadband Adoption, Computer Ownership Vary by Race, Ethnicity in the U.S.* Washington, DC: Pew Research Center (2021).

Begley, T., and A. Purnanandam. "Color and Credit: Race, Regulation, and the Quality of Financial Services." *Journal of Financial Economics*, 141 (2021), 48–65.

Ben-Shahar, O., and C. Schneider. *More than You Wanted to Know: The Failure of Mandated Disclosure*. Princeton, NJ: Princeton University Press (2014).

Bowman, D., and D. Narayandas. "Managing Customer-Initiated Contacts with Manufacturers: The Impact on Share of Category Requirements and Word-of-Mouth Behavior." *Journal of Marketing Research*, 38 (2001), 281–297.

Buchak, G.; G. Matvos; T. Piskorski; and A. Seru. "Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks." *Journal of Financial Economics*, 130 (2018), 453–483.

California Reinvestment Committee. "Five Steps to Community Reinvestment Success: A How-to Manual for Community Reinvestment Campaigns." Available at http://www.calreinvest.org/system/resources/W1siZiIsIjIwMTIvMDYvMTgvMTNfNDVfNDBfMjM0XzE4NC5wZGYiXV0/184.pdf (2001).

California Reinvestment Committee. "Comment Letter on CFPB Request for information Regarding Bureau Public Reporting Practices of Consumer Complaint information." Docket Number CFPB-2018-0006 (2018).

Campbell, J. "Household Finance." *Journal of Finance*, 61 (2006), 1553–1604.

Campbell, J. "Restoring Rational Choice: The Challenge of Consumer Financial Regulation." *American Economic Review*, 106 (2016), 1–30.

Campbell, J.; H. Jackson; B. Madrian; and P. Tufano. "Consumer Financial Protection." *Journal of Economic Perspectives*, 25 (2011), 91–114.

Center for Capital Markets Competitiveness. "Comment Letter on Disclosure of Consumer Complaint Data." Docket Number CFPB-2012-0023 (2012).

CFPB. "Disclosure of Consumer Complaint Data." Docket No. CFPB-2012-0023. Notice of Proposed Policy Statement. *Federal Register*, 77 (2012), 37616–37617.

CFPB. "Disclosure of Consumer Complaint Data." Docket No. CFPB-2012-0023. Final Policy Statement. *Federal Register*, 78 (2013), 21218–21226.

CFPB. "Disclosure of Consumer Complaint Narrative Data." Docket No. CFPB-2014-0016. Final Policy Statement. *Federal Register*, 80 (2015), 15572–15583.

Chevalier, J., and D. Mayzlin. "The Effect of Word of Mouth on Sales: Online Book Reviews." *Journal of Marketing Research*, 43 (2006), 345–354.

Conlon, D., and N. Murray. "Customer Perceptions of Corporate Responses to Product Complaints: The Role of Explanations." *Academy of Management Journal*, 39 (1996), 1040–1056.

Consumer Mortgage Coalition. "Comment Letter on Disclosure of Consumer Complaint Data." Docket Number CFPB-2012-0023 (2012).

Cortes, K., and P. Strahan. "Tracing out Capital Flows: How Financially Integrated Banks Respond to Natural Disasters." *Journal of Financial Economics*, 125 (2017), 182–199.

Cortez, N. "Agency Publicity in the Internet Era." SMU Dedman School of Law Legal Studies Research Paper No. 337 (2015).

De Langhe, B.; P. Fernbach; and D. Lichtenstein. "Navigating by the Stars: Investigating the Actual and Perceived Validity of Online User Ratings." *Journal of Consumer Research*, 42 (2016), 817–833.

Defusco, A.; S. Johnson; and J. Mondragon. "Regulating Household Leverage." *Review of Economics Studies*, 87 (2020), 914–958.

Dellavigna, S. "Psychology and Economics: Evidence from the Field." *Journal of Economic Literature*, 47 (2009), 315–372.

Dou, Y. "The Spillover Effect of Consolidating Securitization Entities on Small Business Lending." *Accounting Review*, 96 (2021), 207–229.

Dou, Y.; J. Jagtiani; J. Ronen; and R. Maingi. "The Credit Card Act and Consumer Debt Structure." *Journal of Law, Finance, and Accounting* 7 (2022), 91–126.

https://doi.org/10.1017/S0022109023000613 Published online by Cambridge University Press

Dou, Y., and Y. Zou. "The Real Effect of Geographic Lending Disclosure on Banks." Working Paper, New York University and George Washington University (2019).

Duguay, R.; T. Rauter; and D. Samuels. "The Impact of Open Data on Public Procurement." Working Paper, University of Chicago (2022).

Egan, M.; G. Matvos; and A. Seru. "The Market for Financial Adviser Misconduct." *Journal of Political Economy*, 127 (2019), 233–295.

Fleming, M. "Making the Most of 2013." *Market Pulse*, 2 (2013), 1–12. Available at https://www.corelogic.com/downloadable-docs/marketpulse_2013-february.pdf.

Fornell, C.; F. Morgeson; and G. Hult. "Stock Returns on Customer Satisfaction on Beat the Market: Gauging the Effect of a Marketing Intangible." *Journal of Marketing*, 80 (2016), 92–107.

Fornell, C., and B. Wernerfelt. "Defensive Marketing Strategy by Customer Complaint Management: A Theoretical Analysis." *Journal of Marketing Research*, 24 (1987), 337–346.

Fung, A.; D. Weil; M. Graham; and E. Fagotto. "The Political Economy of Transparency: What Makes Disclosure Policies Effective?" Working Paper, Harvard University (2004).

Fuster, A.; M. Plosser; and J. Vickery. "Does CFPB Oversight Crimp Credit?" Federal Reserve Bank of New York Staff Reports No. 857 (2021).

Gao, J.; K. Kleiner; and J. Pacelli. "Credit and Punishment: Are Corporate Bankers Disciplined for Risk-Taking?" *Review of Financial Studies*, 33 (2020), 5706–5749.

Gilje, E.; E. Loutskina; and P. Strahan. "Exporting Liquidity: Branch Banking and Financial Integration." *Journal of Finance*, 71 (2016), 1159–1184.

Griffin, J.; S. Kruger; and G. Maturana. "Do Labor Markets Discipline? Evidence from RMBS Bankers." *Journal of Financial Economics*, 133 (2019), 726–750.

Gruber, J. "The Incidence of Mandated Maternity Benefits." *American Economic Review*, 84 (1994), 622–642.

Guiso, L.; A. Pozzi; A. Tsoy; L. Gambacorta; and Mistrulli. "The Cost of Steering in Financial Markets: Evidence from the Mortgage Market." *Journal of Financial Economics* 143 (2022), 1209–1226.

Gurun, U.; G. Matvos; and A. Seru. "Advertising Expensive Mortgages." *Journal of Finance*, 71 (2016), 2371–2416.

Gurun, U.; N. Stoffman; and S. Yonker. "Trust Busting: The Effect of Fraud on Investor Behavior." *Review of Financial Studies*, 31 (2018), 1341–1376.

Hayes, R.; F. Jiang; and Y. Pan. "Voice of the Customers: Local Trust Culture and Consumer Complaints to the CFPB." *Journal of Accounting Research*, 59 (2021), 1077–1121.

Homburg, C., and A. Furst. "How Organizational Complaint Handling Drives Customer Loyalty: An Analysis of the Mechanistic and the Organic Approach." *Journal of Marketing*, 69 (2005), 95–114.

Huang, J. "The Customer Knows Best: The Investment Value of Consumer Opinions." *Journal of Financial Economics*, 128 (2018), 164–182.

Imbens, G., and J. Wooldridge. "What's New in Econometrics?" NBER Lecture Notes (2007). Available at http://www.nber.org/wne/lect_10_diffindiffs.pdf.

Inderst, R., and M. Ottaviani. "How (Not) to Pay for Advice: A Framework for Consumer Financial Protection." *Journal of Financial Economics*, 105 (2012), 393–411.

Jin, G., and P. Leslie. "The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards." *Quarterly Journal of Economics*, 118 (2003), 409–451.

Keys, B.; D. Pope; and J. Pope. "Failure to Refinance." *Journal of Financial Economics*, 122 (2016), 482–499.

Knox, G., and R. Van Oest. "Customer Complaints and Recovery Effectiveness: A Customer Base Approach." *Journal of Marketing*, 78 (2014), 42–57.

Lacko, J., and J. Pappalardo. "Improving Consumer Mortgage Disclosures: An Empirical Assessment of Current and Prototype Disclosure Forms." Staff Report, Federal Trade Commission Bureau of Economics (2007).

Lacko, J., and J. Pappalardo. "The Failure and Promise of Mandated Consumer Mortgage Disclosures: Evidence from Qualitative Interviews and a Controlled Experiment with Mortgage Borrowers." *American Economic Review: Papers & Proceedings*, 100 (2010), 516–521.

Lee, Y.; K. Hosanagar; and Y. Tan. "Do I Follow My Friends or the Crowd? Information Cascades in Online Movie Ratings." *Management Science*, 61 (2015), 2242–2258.

Liu, X.; D. Lee; and K. Srinivasan. "Large-Scale Cross-Category Analysis of Consumer Review Content on Sales Conversion Leveraging Deep Learning." *Journal of Marketing Research*, 56 (2019), 918–943.

Luo, X. "Consumer Negative Voice and Firm-Idiosyncratic Stock Returns." *Journal of Marketing*, 71 (2007), 75–88.

Luo, X. "Quantifying the Long-Term Impact of Negative Word of Mouth on Cash Flows and Stock Prices." *Marketing Science*, 28 (2009), 148–165.

Lusardi, A., and P. Tufano. "Debt Literacy, Financial Experiences, and Overindebtedness." *Journal of Pension Economics & Finance*, 14 (2015), 332–368.
Ma, L.; B. Sun; and S. Kekre. "The Squeaky Wheel Gets the Grease—An Empirical Analysis of Customer Voice and Firm Intervention on Twitter." *Marketing Science*, 34 (2015), 627–645.
Martin, M. "Computer and Internet Use in the United States: 2018. American Community Survey Reports." U.S. Census Bureau (2021).
Mian, A., and A. Sufi. "Fraudulent Income Overstatement on Mortgage Applications during the Credit Expansion of 2002 to 2005." *Review of Financial Studies*, 30 (2017), 1832–1864.
Mukamel, D., and A. Mushlin. "The Impact of Quality Report Cards on Choice of Physicians, Hospitals, and HMOs." *Joint Commission Journal on Quality Improvement*, 27 (2001), 20–27.
Navarro-Martinez, D.; L. Salisbury; K. Lemon; N. Stewart; W. Mathews; and A. Harris. "Minimum Required Payment and Supplemental Information Disclosure Effects on Consumer Debt Repayment Decisions." *Journal of Marketing Research*, 48 (2011), S60–S70.
Newman, K., and E. Wyly. "Geographies of Mortgage Market Segmentation: The Case of Essex County, New Jersey." *Housing Studies*, 19 (2004), 53–83.
Nickell, S. "Biases in Dynamic Models with Fixed Effects." *Econometrica*, 49 (1981), 1417–1426.
Pence, K. "Foreclosing on Opportunity: State Laws and Mortgage Credit." *Review of Economics and Statistics*, 88 (2006), 177–182.
Pischke, J. "Empirical Methods in Applied Economics Lecture Notes" (2005). Available at http://econ.lse.ac.uk/staff/spischke/ec524/evaluation3.pdf.
Rauter, T. "The Effect of Mandatory Extraction Payment Disclosures on Corporate Payment and Investment Policies Abroad." *Journal of Accounting Research*, 58 (2020), 1075–1116.
Raval, D. "Which Communities Complain to Policymakers? Evidence from Consumer Sentinel." *Economic Inquiry*, 58 (2020), 1628–1642.
Richins, M. "Negative Word-of-Mouth by Dissatisfied Consumers: A Pilot Study." *Journal of Marketing*, 47 (1983), 68–78.
Rubin, D. B. "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies." *Journal of Educational Psychology*, 66 (1974), 688–701.
Schipper, K., and R. Thompson. "The Impact of Merger-Related Regulations on the Shareholders of Acquiring Firms." *Journal of Accounting Research*, 21 (1983), 184–221.
Sefcik, S., and R. Thompson. "An Approach to Statistical-Inference in Cross-Sectional Model with Security Abnormal Returns as Dependent Variable." *Journal of Accounting Research*, 24 (1986), 316–334.
Seira, E.; A. Elizondo; and E. Laguna-Muggenburg. "Are Information Disclosures Effective? Evidence from the Credit Card Market." *American Economic Journal: Economic Policy*, 9 (2017), 277–307.
Squires, G.. "The Rough Road to Reinvestment." In *Organizing Access to Capital: Advocacy and the Democratization of Financial Institutions*. Philadelphia: Temple University Press (2003).
Stango, V., and J. Zinman. "Fuzzy Math, Disclosure Regulation, and Market Outcomes: Evidence from Truth-in-Ending Reform." *Review of Financial Studies*, 24 (2011), 506–534.
Stango, V., and J. Zinman. "Limited and Varying Consumer Attention: Evidence from Shocks to the Salience of Bank Overdraft Fees." *Review of Financial Studies*, 27 (2014), 990–1030.
Stanton, R.; J. Walden; and N. Wallace. "The Industrial Organization of the U.S. Residential Mortgage Market." *Annual Review of Financial Economics*, 6 (2014), 259–288.
Tang, V. W. "Wisdom of Crowds: Cross-Sectional Variation in the Informativeness of Third-Party-Generated Product Information on Twitter." *Journal of Accounting Research*, 56 (2018), 989–1034.
Woodward, S., and R. Hall. "Diagnosing Consumer Confusion and Sub-Optimal Shopping Effort: Theory and Mortgage-Market Evidence." *American Economic Review*, 102 (2012), 3249–3276.
Zelizer, V. *The Social Meaning of Money*. Princeton, NJ: Princeton University Press (1997).