Learning from peers: Evidence from disclosure of consumer complaints

Yiwei Dou [a], Mingyi Hung [b,*], Guoman She [c], Lynn Linghuan Wang [c]

[a] *Stern School of Business, New York University, NY, USA*
[b] *School of Business and Management, Hong Kong University of Science and Technology, Hong Kong, China*
[c] *Faculty of Business and Economics, University of Hong Kong, Hong Kong, China*

ARTICLE INFO

ABSTRACT

In 2013, the U.S. Consumer Financial Protection Bureau released a database of consumer complaints filed against banks under its supervision ("CFPB banks"). We find that after the disclosure, rival banks exhibit a greater increase in mortgage approval rates in markets with more intensive mortgage complaints about CFPB banks. The effect is weaker when rivals have more expertise in the local market, are less concerned about credit risk due to mortgage sales, and locate in areas with more alternative information about the CFPB banks. The effect is concentrated in severe complaints and complaints related to loan underwriting practices. In addition to approving more loans, rivals also open more branches and are more likely to post a job opening in these markets. The findings suggest that these banks learn from the nonfinancial disclosures about operational deficiencies of peers (i.e., CFPB banks) in local markets, which alleviates their adverse selection concern about expanding.

© 2023 Elsevier B.V. All rights reserved.

1. Introduction

A fundamental question in accounting research is how disclosure reveals a firm's proprietary information to rivals and facilitates their strategic decisions (Roychowdhury et al., 2019). While firms often comprise multiple business units competing in different local markets, disaggregated financial information for these units is not typically publicly available to their local rivals (Bens et al., 2011). By contrast, granular nonfinancial information for the local business unit, such as customer reviews, is prevalent. The last two decades have witnessed a proliferation of online platforms that allow customers to share their experiences with products and services. Research shows that these opinions have predictive power, above and beyond financial information, concerning firms' fundamentals and stock returns (Chevalier and Mayzlin, 2006; Luca and Zervas, 2016; Huang, 2018; Tang, 2018). Using regulator-disclosed consumer complaints, this paper examines how firms take advantage of the complaint disclosures against peers in mortgage markets.

* Corresponding author.
   E-mail addresses: yd18@stern.nyu.edu (Y. Dou), acmy@ust.hk (M. Hung), gshe@hku.hk (G. She), lynn.wang@hku.hk (L.L. Wang).

ARTICLE IN PRESS

Y. Dou, M. Hung, G. She et al.   Journal of Accounting and Economics xxx (xxxx) xxx

The Consumer Financial Protection Bureau (CFPB) was established by the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act in the U.S. In 2011, the bureau started accepting consumer complaints about the financial products and services of banks under its supervision ("CFPB banks"). In 2013, it publicly released the complaint data, which contain detailed information, such as the banks' names, submission dates, complainants' ZIP Codes, and types of products and issues. The disclosure of the complaint data is intended to ensure that markets for consumer financial products and services "operate transparently and efficiently" (CFPB, 2013). However, the CFPB banks and their trade associations strongly oppose this public disclosure due to the proprietary nature of the information and the potential harm to their competitive positions.[1]

We investigate how disclosing consumer complaints against CFPB banks in a local mortgage market informs rival banks and thereby influences the rivals' credit supply in the same market. As of the disclosure date in 2013, the CFPB consumer complaint database drew about a hundred thousand complaints, 53.6% of which are about mortgages, with issues arising from loan underwriting, servicing, and collection. Home mortgages also account for about a quarter of credit market assets of banks by the end of 2012.[2] In addition, to conduct an effective test of changes to credit supply, it is important to control for credit demand. The Home Mortgage Disclosure Act (HMDA) database, which contains records of mortgage applications and their approval status, allows us to compute the approval rates. These rates help us isolate the supply effect since the denominator accounts for loan demand (Munnell et al., 1996; Loutskina and Strahan, 2009; Dou et al., 2018).

A bank can learn both peer-specific and market-wide information from disclosures of mortgage complaints against its peers (i.e., CFPB banks), the net effect of which on its lending decisions is unclear. On the one hand, intensive mortgage complaints in a local market reveal peer-specific information on their deficiencies in serving the local market, such as inappropriate underwriting practices, poor loan servicing, and inadequate loan collection and foreclosure (CFPB, 2016; Dou and Roh, 2023). The deficiencies uncover peers' weaknesses and thus can increase the bank's willingness to lend in the same area. For example, a bank may deny loan applications due to the concern that bad borrowers previously rejected by peer banks approach them (Dell'Ariccia et al., 1999; Marquez, 2002; Sutherland, 2018). This adverse selection concern is alleviated when intensive complaints indicate bad customer service or weak screening processes of peer banks. In other words, unfamiliar applicants are less likely to be "lemons" since they are more likely to be switching due to poor service at peer banks or be incorrectly disapproved by peer banks with poor screening ability. As a result, the reduced concern motivates the bank to expand mortgage supply. This is consistent with the view from practitioners that advocates using the complaint database to "leverage competitor weaknesses by taking strategic action to win business".[3]

On the other hand, more intensive mortgage complaints may suggest a higher proportion of consumers in the local market who are costly to serve (CFPB, 2016; Raval, 2020). This market-wide information reduces the perceived lending profitability of all banks, potentially prompting rival banks to reduce mortgage lending. In addition, the disclosures may not inform rival banks if they already have sufficient information about CFPB banks and market conditions before the information release or if the disclosures are of low quality. Thus, whether and how the public disclosure of consumer complaints influences rival banks' mortgage lending are ultimately empirical questions.

Our setting offers several advantages for investigating the research question. First, the release of the complaint database represents a shock to the information set from which rival banks can learn. By examining the lending changes of rival banks around the shock, we can remove the influences of slow-moving or persistent confounding factors. While many online platforms (e.g., Yelp) also inform competitors, such a shock typically does not exist, making it difficult to tease out the effect of disclosure. Second, the bureau has collected the data since its establishment in 2011 but did not release it to the public until 2013. We can use the time in-between as the pre-period to better separate the effect of disclosure from the effect of CFPB oversight. Third, for a bank that also receives complaints, parsing out the learning-from-peer effect is challenging since the effect is confounded by its reaction to both complaints against itself and peers' learning about these complaints. Banks with assets below $10 billion are exempt from the CFPB's supervision and thus are not covered by the complaint database ("non-CFPB rivals"). We focus on these banks in our primary analyses, because they are not subject to the confounding issues and the association between their lending changes and disclosed complaints against CFPB banks can be better attributed to their learning.[4]

Our sample consists of 44,948 bank-county-year observations for 3214 unique non-CFPB banks from 2011 to 2015 (two years before and after releasing the mortgage complaint data in 2013). The dependent variable is the annual approval rate measured as the percentage value of mortgage applications approved by a bank in a county-year. The test variable is an interaction term between a county-level intensity of mortgage complaints and an indicator variable for the post-disclosure

---

period. We measure the intensity of mortgage complaints using the total number of mortgage complaints in the county against CFPB banks from 2011 to the year in question divided by the total number of mortgage originations by these banks from 2011 to that year, multiplied by 100. The denominator of this measure accounts for the size of CFPB banks' local operations.

We control for various applicant, bank-county-year, and county-year characteristics and bank-county, bank-year, and state-year fixed effects. These fixed effects account for time-invariant heterogeneity across bank-county pairs (e.g., the distance from a county to a bank's headquarters), time-varying bank characteristics, and legislative and economic changes in a state. The model represents a generalized difference-in-differences specification with a continuous treatment variable (Angrist and Pischke, 2009). It essentially permits a comparison of non-CFPB rivals' approval rates within the same state-year across counties influenced differently by the disclosure.

The results indicate a greater increase in non-CFPB rivals' mortgage approval rates after the disclosure in the counties where the CFPB banks receive more intensive complaints. To evaluate the economic significance, we compute the standard deviation of the approval rates for each bank-county and take the average across all bank-counties. Relative to this average within-bank-county standard deviation, an interquartile increase in the intensity of mortgage complaints against CFPB banks is associated with an 8.7% increase in mortgage approval rates ($1.25 billion in mortgage credit).[5] Consistent with the parallel trends assumption, the effect occurs in subsequent years but not before or during the release year. Our results are robust to using alternative samples (e.g., matched pairs of contiguous counties) and alternative measures of peer consumer complaints. The results support the view that banks learn from the disclosures about peers' operational deficiencies and therefore expand their lending.

Next, our cross-sectional analyses show that the documented effect is weaker when non-CFPB rivals have more expertise in the local market and are less concerned about credit risks, as measured by their market share and proportion of mortgages sold, respectively. Consistent with the notion that the disclosure is less useful when there is more alternative information about peers, we find a weaker effect when there are more negative Yelp reviews on CFPB banks. The effect is also concentrated among severe complaints and complaints related to loan underwriting practices, which send a clear signal of service quality and directly reflect screening ability, respectively.

We take several steps to address an alternative explanation that the quality of non-CFPB rivals' applicant pool improves. This improvement may arise from CFPB banks' pullback after the Dodd-Frank Act or consumers' reactions to the disclosure (Fuster et al., 2021; Dou and Roh, 2023). In addition to controlling for applicants' characteristics (e.g., income and loan-to-income ratios), we exclude mortgages insured by the Federal Housing Administration (FHA), the market that CFPB banks retreat from after 2011 (Fuster et al., 2021). To further address CFPB banks' potential pullback, we compute their market share in each county before the Dodd-Frank Act and include this variable's interaction with the indicator for the post-period. We also add controls that capture the approval rates and attributes of received and approved loan applications for CFPB banks. Our inferences continue to hold under these specifications. Our results also do not vary with consumers' use of the disclosures (proxied by Internet searches for "CFPB") and their sophistication (proxied by the proportion of the population with a high school diploma), suggesting that consumers' reactions to the disclosure alone are unlikely to explain our findings.

Additional analyses indicate that non-CFPB rivals in counties with more intensive consumer complaints against CFPB banks increase the number of bank branches and the likelihood of posting a job opening following the disclosure. Relative to the average within-bank-county standard deviation, an interquartile increase in the intensity of mortgage complaints is associated with a 35.6% (13.5%) increase in the number of branches established (likelihood of posting a job opening) by non-CFPB rivals. Consistent with the rivals benefiting from learning about CFPB banks' weaknesses, they experience greater increases in profitability following the disclosure when CFPB banks receive more complaints. Finally, we extend the analysis to CFPB banks with few complaints (CFPB rivals) and find results suggesting that they learn from complaints against other CFPB banks.

We contribute to the literature on the real effects of disclosure by providing new evidence consistent with the learning-from-peers channel (Leuz and Wysocki, 2016; Jayaraman and Wu, 2019; Roychowdhury et al., 2019). Prior studies show that firms learn industry prospects from peers' financial reporting (Durnev and Mangen, 2009; Badertscher et al., 2013; Beatty et al., 2013; Li, 2016; Shroff, 2016). As industry-wide news influences all firms in the same direction, firms learn fewer investment opportunities from peers' weak performance. In contrast, our evidence suggests that firms learn peer-specific news from consumer complaints, which does not concern them directly and has a bearing on them only through their strategic interactions with peers. As such, peers' deficiencies imply more opportunities for firms to expand.

Two recent studies on financial institutions show that lenders mimic loan contract terms disclosed by their peers (Darmouni and Sutherland, 2021; Kang et al., 2021).[6] Our study differs in that we examine a new type of information about peers collected and disclosed by a regulator. Unlike contract terms, rivals cannot directly copy consumer reviews and the

---

[5] Since we are interested in how banks adjust their lending decisions in a county over time, the average within-bank-county standard deviation is more meaningful than the one for a pooled sample, which essentially combines banks with very different business models, geographic focus, etc.

[6] See also the "learning from peer disclosures" in Roychowdhury et al. (2019) for nonbank settings. A related stream of literature examines how firms react to peers' financial reports (Bernard, 2016; Cao et al., 2021; Zou, 2022), patent disclosures (Kim and Valentine, 2021), and clinical trial failure (Krieger, 2021).

complaint contents are difficult to verify (CFPB, 2013). Nevertheless, our evidence suggests that such information in a regulator-maintained database is useful to rivals in alleviating the adverse selection concern and deciding where to expand.

Finally, our study adds to the debate on the public disclosure of the consumer complaint database.[7] Prior studies mainly focus on the effect of CFPB oversight on bank operations (Fuster et al., 2021; Hayes et al., 2021) and the determinants of complaint rates (Raval, 2020; Begley and Purnanandam, 2021). None of these studies examines the effects of the complaint disclosure. As technology is making it easier for the complaint data to be compiled and shared with the public in a timely and reliable way (Charoenwong et al., 2023), understanding consequences of this disclosure policy is crucial. Using a sample of CFPB banks, Dou and Roh (2023) find that the complaint disclosure leads to a greater reduction in mortgage applications to banks with more complaints. We add to this research by examining their rival banks. In light of the prevalence of unsophisticated households, our results suggest that disclosing consumer complaints can improve service quality by accelerating the exit of banks with bad quality and the entry of higher quality banks.[8]

2. Institutional background and empirical predictions

2.1. Institutional background

The CFPB is an independent agency that focuses on consumer financial protection. It has supervisory authority "over banks, thrifts, and credit unions with assets over $10 billion, as well as their affiliates."[9] The bureau collects, investigates, and responds to consumer complaints, and any consumer can submit a complaint against a bank. After confirming a commercial relationship between a consumer and bank, the bureau sends the complaint to the bank for a response within 15 days. In July 2011, the CFPB began accepting credit card complaints and later expanded to complaints about other financial products and services. On June 19, 2012, the CFPB publicly released credit card complaint data by launching a beta version of the Consumer Complaint Database. On March 28, 2013, the database extended to complaints about mortgages dating back to December 1, 2011, and three other financial products dating back to March 1, 2012.[10]

The CFPB consumer complaint database had about one hundred thousand complaints as of the disclosure date in 2013. The database provides the names of the companies that receive complaints and detailed consumer experiences, including submission dates, consumers' ZIP Codes, types of products, and issues. We focus on mortgage complaints, which constitute the majority of complaints (53.6%). The issues of mortgage complaints arise from different stages of a credit life cycle: loan underwriting ("application, originator, mortgage broker," "settlement process and costs," and "credit decision/underwriting"), servicing ("loan servicing, payments, escrow account"), collection ("loan modification, collection, foreclosure"), and others ("other"). Appendix A provides several examples of consumer complaint narratives about the three major issues (loan underwriting, servicing, and collection).[11] In the first example, a family filed a complaint against Bank of America for a lengthy loan origination since "it appeared that underwriting was having challenges in accurately assessing our income and documents." In the second example, a complaint was filed against Citizens Financial Group because the bank failed to complete a home appraisal promptly for applicants with excellent credit records, low debt-to-income ratios, and sufficient down payments. The third example shows a complaint about telephone harassment by Ditech Financial during a grace period for payment. The fourth example is a complaint against U.S. Bancorp for a prolonged process for a previous delinquent borrower to make payment.

The industry vehemently opposed the public disclosure of the mortgage complaint data on the grounds that it reveals a large amount of information about banks' local operations. For example, the first two examples illustrate that consumer complaints likely reveal peer firms' operational deficiencies in loan underwriting. They suggest the weak screening ability of CFPB banks in the local markets.

2.2. Empirical predictions

The disclosure of mortgage complaints can convey two types of information to rival banks. First, the mortgage complaints reveal bank-specific information on CFPB banks' deficiencies in local operations. Consumers' (negative) opinions reflect their dissatisfaction with the bank. Intensive mortgage complaints likely indicate deficiencies, such as low loan underwriting

---

[7] See "CFPB Considers Ending Public Access to Complaints About Banks" by Yuka Hayashi, The Wall Street Journal, April 24, 2018, and "Exclusive: New U.S. consumer watchdog chief to continue review of complaints database, fair lending" by Pete Schroeder and Katanga Johnson, *Reuters*, April 19, 2019.

[8] According to a 2009 survey by the National Financial Capability Study, only 39% of U.S. adults were able to correctly answer all three basic financial literacy questions. See Hastings et al.'s (2013) Table 1 for the questions.

[9] See https://www.consumerfinance.gov/compliance/supervision-examinations/institutions/. While banks below the size threshold generally are exempt from CFPB oversight, some are not because the CFPB has authority over affiliates of banks with assets greater than $10 billion. For example, if a bank holding company owns two depository subsidiaries, one with $15 billion in assets and the other with $5 billion in assets, both will be subject to CFPB oversight.

[10] See https://www.consumerfinance.gov/about-us/blog/releasing-complaint-data-about-credit-cards-mortgages-student-loans-bank-accounts-services-and-other-consumer-loans/.

[11] On June 25, 2015, the CFPB 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). In particular, the CFPB changed the disclosure of 5-digit ZIP Codes to protect consumer privacy. It discloses the 3-digit ZIP Code if the 5-digit ZIP Code area contains fewer than 20,000 people, and discloses no ZIP Code if the 3-digit ZIP Code area contains fewer than 20,000 people.

quality, inappropriate mortgage service practices, poor recruitment and employee training, and even violations of consumer financial protection laws (CFPB, 2016). Consistent with the notion that consumer complaints reveal information on firm value, Huang (2018) finds that consumer opinions predict future returns. Similarly, intensive mortgage complaints likely reflect operational deficiencies and poor service quality, which can directly affect bank value. Dou and Roh (2023) find that CFPB banks' stock prices react negatively to the public release of the database, and the magnitude of the negative reaction increases with the intensity of mortgage complaints.

Economic theory suggests that it is more profitable to compete against weaker players (Milgrom and Roberts, 1982a, 1982b; Fudenberg and Tirole, 1986). The disclosure of more mortgage complaints against CFPB banks increases rival banks' perceived benefits of lending in the same area. For example, a bank faces an adverse selection problem: they may deny loan applications due to the concern that bad borrowers previously rejected by peer banks approach them (a "winner's curse"; Dell'Ariccia et al., 1999; Marquez, 2002; Sutherland, 2018). This concern is mitigated if borrowers apply to the bank due to poor service at its peers, as revealed by more intensive complaints. The importance of this concern also decreases when more intensive mortgage complaints reflect weaker screening ability of CFPB banks, which are more likely to disapprove good mortgage applicants. The alleviation of rival banks' adverse selection concern increases their credit supply.

Second, mortgage complaints against CFPB banks might reveal market-wide information about borrowers' characteristics in the local market. Raval (2020) and Begley and Purnanandam (2021) show that consumers with lower income, educational attainment, and creditworthiness are more prone to complaining. Intensive mortgage complaints may suggest that consumers in the local market are either unable to make the payment or are costly to serve. As such, the revelation of intensive mortgage complaints against CFPB banks might reduce the expected profitability of lending for all banks in the local market. Consequently, rival banks may reduce their mortgage lending.

Third, the disclosures may not inform rival banks if they are already well informed about competitors and market conditions through frequent local interactions before the release of the database (Smith, 1987; Biais and Gollier, 1997; Berger and Hann, 2007) or if the disclosures are of low quality. This leads to our hypothesis, which is non-directional.

Hypothesis. *Rival banks exhibit either larger increases or larger decreases in their mortgage lending following the release of more consumer complaints against CFPB banks in the local market.*

3. Sample, data, and research design

3.1. Sample and data

We first obtain data on mortgage complaints from the consumer complaint database for 2011–2015 (i.e., two years before and two years after the disclosure year). This sample period is after the establishment of the CFPB and thus helps us tease out the effect of CFPB oversight. After focusing on complaints with valid ZIP Codes and matching these complaints to the CFPB banks covered by the HMDA database (under agency code 9 for CFPB), we obtain 79,004 mortgage complaints filed against 67 CFPB banks from 2011 to 2015, which include 32,009 mortgage complaints as of the disclosure date in 2013. The mortgage literature typically treats a county as a local market (Pence, 2006; Gilje et al., 2016; Cortés and Strahan, 2017; Mian and Sufi, 2017). As such, we use consumers' ZIP Codes in the complaint database and compute the total number of complaints against CFPB banks for each county-year.

Next, we obtain all mortgage applications to banks from the HMDA database from 2011 to 2015. The HMDA database provides information about the years of loan applications; lenders' names; loan characteristics such as the dollar amount, type, and purpose; applicant's demographic information; and whether a loan is approved. We require an application to either be approved or denied. In addition, we restrict the applications to those with loan amounts greater than $1000 because loan amounts lower than this threshold are rounded up to $1000 (Dell'Ariccia et al., 2012; Dou et al., 2018). This initial sample consists of 29,985,719 mortgage loan applications from 836,210 bank-county-years (4,764 unique banks).

In our primary analyses, we focus on the lending decisions of non-CFPB rivals. This sample restriction results in 9,509,569 loan applications from 561,190 bank-county-years and 4,658 unique non-CFPB rivals. In order to ensure that a bank is an economically important (i.e., non-trivial) player in a county, we restrict our sample to bank-county-years with at least 40 loan applications. Such a requirement also ensures a meaningful and robust computation of approval rates.[12] Loan applications to these bank-county-years account for 76% of those to all non-CFPB rivals, suggesting that our sample is representative. The results are not sensitive to this cutoff (see Section 4.5.1).

Finally, we obtain financial data from FR Y–9C for bank holding companies and Call Reports for commercial banks. County characteristics such as income per capita are from the Bureau of Economic Analysis, and unemployment rates are from the Bureau of Labor Statistics. Our primary sample consists of 44,948 non-CFPB bank-county-year observations that meet the data requirements of our primary analysis, covering 3,214 unique banks from 2011 to 2015. We outline our sample selection procedure for non-CFPB banks in Panel A of Table 1. In Panel B, we report the sample distribution for the main analyses by year. The numbers of observations are reasonably stable over time, in terms of both bank-county-years and bank-years.

---

[12] Statisticians suggest a minimum sample size of 30 observations so that the distribution of the sample mean approximates a normal distribution according to the central limit theorem (Berenson et al., 2018; Agresti, 2021).

Table 1
Sample selection and distribution.

Panel A: Sample selection of non-CFPB rivals			
Selection criteria	# of Loan applications	# of Bank-county -years	# of Banks
HMDA loans with the amount larger than $1000, and supervised by the OCC, FRS, FDIC, or CFPB from 2011 to 2015	29,985,719	836,210	4,764
Restrict the initial sample to non-CFPB rivals	9,509,569	561,190	4,658
Require at least 40 mortgage applications for each bank-county-year observation	7,132,236	45,959	3,230
Require bank-county-year observations to have valid values for control variables	6,997,425	44,948	3,214

Panel B: Sample distribution by year					
Year	Bank-county-year observations			Bank-year observations	
	Number	Frequency		Number	Frequency
2011	8,364	19%		2,593	20%
2012	10,283	23%		2,662	21%
2013	9,580	21%		2,623	21%
2014	7,852	17%		2,428	19%
2015	8,869	20%		2,414	19%
Total	44,948	100%		12,720	100%

Panel A reports the sample selection procedure. Panel B reports the sample distribution by year.

3.2. Research design

We test our hypothesis by estimating the following difference-in-differences specification:

$$Approval\ Rate(\%)_{i,c,t} = \beta_1 PeerCPL_{CFPB}(\%)_{c,t} + \beta_2 PeerCPL_{CFPB}(\%)_{c,t} \times Post_t + Controls + \nu_{i,c} + \eta_{i,t} + \tau_{s,t} + \varepsilon_{i,c,t}, \tag{1}$$

where i denotes non-CFPB rivals, and $c, t,$ and s denote counties, years, and states, respectively. *Approval Rate*$(\%)_{i,c,t}$ is the approval rate measured as the percentage of the number of mortgage applications that a non-CFPB rival approves in a county-year. Compared with the number of loan originations, this measure better captures credit supply as the denominator (the number of applications) effectively controls for the effect of credit demand (Munnell et al., 1996; Loutskina and Strahan, 2009; Dou et al., 2018; Aobdia et al., 2021).

The indicator *Post* is set to one for years during and after the release of the mortgage complaint data (i.e., 2013−2015), and zero otherwise. *PeerCPL*$_{CFPB}(\%)$ is the total number of mortgage complaints against CFPB banks in the county from 2011 to the year in question, divided by the total number of mortgage originations by these banks from 2011 to that year, multiplied by 100.[13] As the complaint database is updated daily after the release, our dynamic measure of complaint intensity allows rival banks to base their decisions on up-to-date information in the database. For instance, as argued by the American Financial Services Association (2012), banks can analyze the amount, content, and trend (i.e., temporal changes) of complaints against their peers using the entire dataset.

We include three sets of fixed effects in Equation (1): bank-county ($\nu_{i,c}$), bank-year ($\eta_{i,t}$), and state-year ($\tau_{s,t}$). The bank-county fixed effects account for time-invariant heterogeneity across bank-county pairs, such as the distance from a county to a bank's headquarters or its customer focus. The bank-year fixed effects account for time-varying bank characteristics (e.g., capital adequacy and bank liquidity). The state-year fixed effects control for time-varying state-level factors, such as regulatory enforcement. The main effect of *Post* is absorbed by the bank-year fixed effects.

Our model represents a generalized difference-in-differences specification with a continuous treatment variable (Angrist and Pischke, 2009). This specification enables us to compare non-CFPB rivals' approval rates within the same state-year across counties influenced differently by the disclosure. Coefficient β_1 captures rivals' responses to mortgage complaints against CFPB banks that were collected but unreleased by the bureau. We are interested in β_2, the coefficient on *PeerCPL*$_{CFPB}(\%)\times$ *Post*. It captures the effect of disclosing one more unit of complaint intensity against CFPB banks on changes in non-CFPB rivals' approval rates around the publication of the complaint data. Since our dependent variable is measured at the bank-county-year level and our independent variable of interest, *PeerCPL*$_{CFPB}(\%)\times$ *Post*, is defined at the county-year level, we use robust standard errors clustered by county to adjust for correlation among residuals in a county.

In our full model, we control for various time-varying borrower-level, loan-level, bank-level, and county-level variables used in prior studies to explain approval rates (Loutskina and Strahan, 2009; Xie, 2016; Dou et al., 2018; Aobdia et al., 2021). Specifically, we include the following borrower characteristics: 1) *Applicant Income*, the natural logarithm of the average

---

[13] We divide the total number of mortgage originations in 2011 by 12 because the coverage of mortgage complaints begins on December 1, 2011.

applicant income, 2) *Loan to Income*, the average loan-to-income ratio, 3) *Gender*, the fraction of female applicants, and 4) *Race*, the fraction of white applicants. We include the following loan and bank characteristics: 1) *Not Secured*, the fraction of loans not secured by a lien, 2) *Loan Type*, the fraction of conventional loans, 3) *Property Type*, the fraction of property that is a one-to-four family house, and 4) *Branch Presence*, the presence of a bank branch in the county. We also control for the following county characteristics: 1) *Market Size*, the total dollar amount of mortgage applications in the county, 2) *Income Growth(%)*, the growth rate of income per capita multiplied by 100, and 3) *Unemployment(%)*, unemployment rates multiplied by 100.

3.3. Descriptive statistics

Table 2 reports the descriptive statistics for the variables we use in the primary analyses. The non-CFPB banks in our sample approve about 85% of loan applications. The complaint intensity, $PeerCPL_{CFPB}(\%)$, has a mean of 0.362% and a standard deviation of 0.390%. Fig. 1 is a heatmap of the geographic distribution of the complaint intensity, $PeerCPL_{CFPB}(\%)$, measured in 2015. While counties that generate the most complaints are concentrated in California, Florida, and New York, counties in other states (e.g., Georgia, Texas, and Arizona) also show non-trivial numbers of complaints. We also compute the number of new complaints for each bank-county-year observation in our sample (N = 44,948) and find that the mean, median, and standard deviation of this variable are 32.977, 3.000, and 106.890, respectively.[14]

Table 2 shows the mean value of the natural logarithm of average applicant income is 4.550, which translates to an annual income of \$94,632 (= $e^{4.550}$ × 1000), and the average loan-to-income ratio is 1.995. We find that 25.1% of applicants are female, and 83.1% are white. In addition, 3.5% of the loans are not secured, 85.9% are conventional loans, and 95.4% are loans for one-to-four family housing. For 67.8% of our bank-county-year observations, the bank has at least one branch. This is unsurprising since we require a bank-county-year to have at least 40 mortgage applications to exclude trivial players. The average market size is 13.214, indicating about \$548 million (= $e^{13.214}$ × 1000) in mortgage applications in total in a county. These statistics are generally consistent with prior research (e.g., Loutskina and Strahan, 2009). We winsorize all continuous variables at the top and bottom 1% of the distribution.

4. Results

4.1. Hypothesis test

Table 3 presents the results of testing our hypothesis. We first include only the fixed effects in the regression as control variables to alleviate the concern that including covariates affected by the treatment may undermine the ability to draw clear inferences (Gormley and Matsa, 2014; Imbens and Rubin, 2015). The results in column (1) show that the coefficient on $PeerCPL_{CFPB}(\%)$ is statistically indistinguishable from zero, consistent with the expectation that rivals' responses to mortgage

Table 2
Summary statistics.

Variable	N	Mean	Std. dev.	Q1	Median	Q3
Dependent variable						
Approval Rate(%)	44,948	84.997	11.372	79.808	87.500	93.182
Test variables						
PeerCPL$_{CFPB}$(%)	44,948	0.362	0.390	0.000	0.286	0.538
Post	44,948	0.585	0.493	0.000	1.000	1.000
Bank-county-year variables						
Applicant Income	44,948	4.550	0.339	4.305	4.514	4.753
Loan to Income	44,948	1.995	0.628	1.560	1.967	2.409
Gender	44,948	0.251	0.081	0.196	0.247	0.301
Race	44,948	0.831	0.158	0.770	0.878	0.944
Not Secured	44,948	0.035	0.080	0.000	0.000	0.024
Loan Type	44,948	0.859	0.193	0.783	0.952	1.000
Property Type	44,948	0.954	0.080	0.946	0.986	1.000
Branch Presence	44,948	0.678	0.467	0.000	1.000	1.000
County-year variables						
Market Size	44,948	13.214	1.805	11.800	13.230	14.604
Income Growth(%)	44,948	3.630	2.930	1.830	3.635	5.257
Unemployment(%)	44,948	6.975	2.361	5.300	6.745	8.400

This table reports the summary statistics of variables used in the main analyses. Appendix B provides the variable definitions.

---

[14] For the 10,155 unique county-years of our sample, the mean, median, and standard deviation of the number of new complaints are 7.759, 0.000, and 39.602, respectively. These statistics are lower than those at the bank-county-year level since larger counties tend to have both more complaints and more observations.
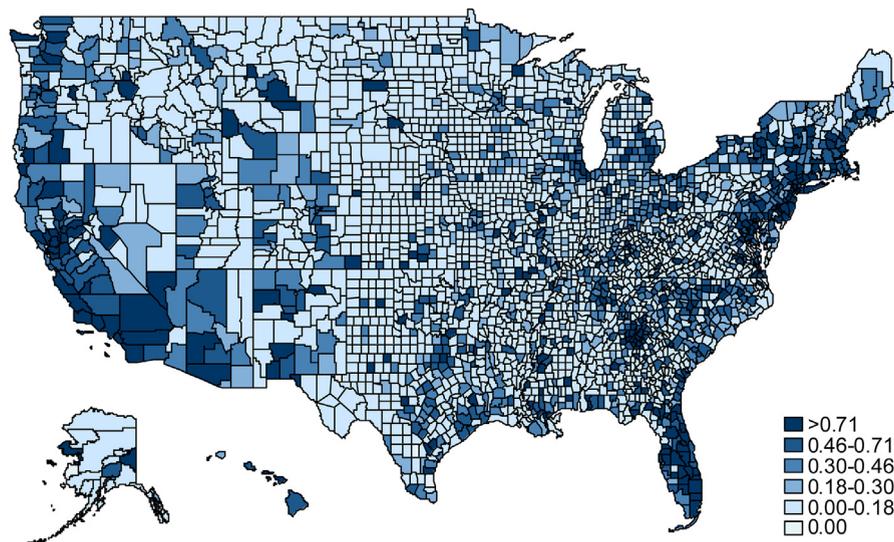
Fig. 1. Geographic distribution of peer consumer complaints. This heatmap shows the geographic distribution of $PeerCPL_{CFPB}(\%)$ in 2015, the cumulative number of mortgage complaints in a county against CFPB banks from 2011 to 2015, scaled by the cumulative number of mortgage originations by these banks in the county during the same period, multiplied by 100.

complaints against CFPB banks are muted in the absence of disclosure. The coefficient on $PeerCPL_{CFPB}(\%) \times Post$ is significantly positive (0.810 with a two-tailed p-value <0.01). The result suggests that rival banks increase their loan approval rates when observing more complaints against CFPB banks. We then control for a host of the applicant, loan, and county characteristics and find similar results in column (2): the coefficient on $PeerCPL_{CFPB}(\%) \times Post$ remains significantly positive (0.705 with a two-tailed p-value <0.01).

This effect is economically meaningful in three respects. First, we compute the average within-bank-county standard deviation by taking the standard deviation of the approval rates for each bank-county and averaging it across all bank-counties. Relative to the within-bank-county standard deviation of approval rates (4.364%), moving $PeerCPL_{CFPB}(\%)$ from the first to the third quartile increases the approval rate by 8.7% (=0.705 × 0.538%/4.364%). Second, as the total mortgage applications to non-CFPB rivals in 2012 amounted to $329 billion, the increase in approval rates (0.38% = 0.705 × 0.538%) translates into a $1.25 billion increase in mortgage credit, a significant amount for households. Finally, Loutskina and Strahan (2009) document that moving the balance sheet liquidity of banks from the first to the third quartile increases the approval rate by 0.6%, in an order of magnitude similar to the effect documented in our study.

Regarding control variables, we find a higher approval rate for applications with higher income and lower loan-to-income ratios, consistent with banks being more willing to grant loans to those with lower credit risk. Unsurprisingly, unsecured loan applications are less likely to be approved. Consistent with the literature, applications for conventional loans and loans for one-to-four family housing are more likely to be approved.

The critical identification assumption underlying our research design is that the trends of non-CFPB rivals' lending decisions would be the same in the absence of the complaint disclosure. To assess the assumption, we replace $PeerCPL_{CFPB}(\%) \times Post$ with the interaction terms between $PeerCPL_{CFPB}(\%)$ and year indicators for the years 2012−2015. The omitted year 2011 serves as the benchmark period. Columns (3) and (4) of Table 3 show the results. In support of the parallel trends assumption, we find that $PeerCPL_{CFPB}(\%) \times Year2012$ is insignificant at conventional levels. This result suggests that the increase in approval rates of non-CFPB rivals in counties with more intensive complaints against CFPB banks does not occur before the disclosure. In contrast, the observed effect manifests only after the public release of the mortgage complaint data and remains significant after that (i.e., 2014−2015). We also find that $PeerCPL_{CFPB}(\%) \times Year2013$ does not load, although the database was released in 2013. This result suggests that it takes time for non-CFPB rivals to learn from the complaint disclosures.

In sum, the results in Table 3 suggest that non-CFPB rivals increase their mortgage approval rates after the release of the complaint data that reveal intensive complaints against the CFPB banks. These results are consistent with the notion that non-CFPB rivals learn from the disclosures about CFPB banks' operational deficiencies and expand their credit supply.

4.2. Analyses conditional on bank expertise, incentives, and opportunities

To corroborate our inference that non-CFPB rivals learn bank-specific information about CFPB banks from the complaint disclosures, we explore cross-sectional variation in factors underlying the documented effect. The adverse selection concerns in the lending process arise from the information frictions that prevent a bank from effectively evaluating the

Table 3
Disclosure of peer consumer complaints and mortgage approval rates.

Dep. Var. =	Approval Rate(%)			
	(1)	(2)	(3)	(4)
$PeerCPL_{CFPB}(\%)$	−0.101	−0.064	−0.158	−0.150
	(0.227)	(0.220)	(0.264)	(0.257)
$PeerCPL_{CFPB}(\%) \times Post$	0.810***	0.705***		
	(0.274)	(0.271)		
$PeerCPL_{CFPB}(\%) \times Year2012$			0.085	0.184
			(0.410)	(0.403)
$PeerCPL_{CFPB}(\%) \times Year2013$			0.560	0.504
			(0.433)	(0.423)
$PeerCPL_{CFPB}(\%) \times Year2014$			1.156***	1.083**
			(0.447)	(0.438)
$PeerCPL_{CFPB}(\%) \times Year2015$			1.483***	1.445***
			(0.463)	(0.460)
Applicant Income		3.855***		3.863***
		(0.387)		(0.387)
Loan to Income		−1.706***		−1.717***
		(0.260)		(0.260)
Gender		−3.577***		−3.595***
		(0.713)		(0.712)
Race		1.090		1.115
		(0.768)		(0.768)
Not Secured		−15.180***		−15.079***
		(1.816)		(1.816)
Loan Type		2.118**		2.055**
		(0.901)		(0.900)
Property Type		6.620***		6.638***
		(1.613)		(1.611)
Branch Presence		−0.017		−0.027
		(0.312)		(0.312)
Market Size		−0.119		−0.144
		(0.386)		(0.386)
Income Growth(%)		0.006		0.006
		(0.015)		(0.015)
Unemployment(%)		0.014		0.013
		(0.086)		(0.086)
Bank-county FE	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
N (bank-county-years)	44,948	44,948	44,948	44,948
Adj. R^2	0.834	0.839	0.835	0.839

This table reports the effect of disclosing peer consumer complaints on mortgage approval rates. *Approval Rate(%)* is the percentage of the number of mortgage applications that the non-CFPB rival approves in a county-year. *PeerCPL$_{CFPB}$(%)* is the cumulative number of mortgage complaints in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. *Post* is set to one for 2013−2015 and zero for 2011−2012. Appendix B provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

creditworthiness of loan applicants. Thus, we expect the learning effect to be weaker when non-CFPB rivals have more expertise in the local market and are less concerned about credit risk, and when there is more alternative information about CFPB banks' local operations.

We first investigate the variation in non-CFPB rivals' lending experience in the local market. Expert banks, which have a large number of applications in a county, are likely to have little to learn from the complaint disclosures. In contrast, non-expert banks with little lending experience face severe adverse selection concerns and therefore can learn more from the disclosures. We designate rival banks as experts if their county-level market share in 2012 (i.e., the year before the complaint disclosure) is above 10%.[15] Panel A of Table 4 reports the descriptive statistics of the partitioning variables. Column (1) of Panel B shows the estimation of Equation (1) augmented with the interaction term between *PeerCPL$_{CFPB}$(%) × Post* and an indicator for expert banks (*High MktShare$_{Non-CFPB}$*). The main effect of this indicator is absorbed by bank-county fixed effects. Consistent with our prediction, we find that the coefficient on *PeerCPL$_{CFPB}$(%) × Post × High MktShare$_{Non-CFPB}$* is significantly negative.

Second, we explore non-CFPB rivals' incentives to utilize the complaint disclosures by exploiting the extent to which the mortgages are sold. Banks have weaker concerns about adverse selection and thus weaker incentives to use the new information when they tend to transfer credit risk to outsiders via mortgage sales (Keys et al., 2010). For each bank-county-year

---

[15] We use all banks from the HMDA database (i.e., not just those in our sample) to compute market share. The 10% cutoff lies close to the third quartile of the distribution in our final sample (0.092) as reported in Panel A. Results are robust to using the median in our final sample (0.027) as a cutoff.

Table 4
Analyses conditional on bank expertise, incentives, and opportunities.

Panel A: Descriptive statistics on the partitioning variables (N = 44,948)

Variable	Mean	Std. dev.	Q1	Median	Q3
$MktShare_{Non-CFPB}$	0.073	0.109	0.006	0.027	0.092
$Sold_{Non-CFPB}$	0.501	0.350	0.143	0.556	0.826
$Bad\ Yelp\ Review_{CFPB}$	0.037	0.053	0.000	0.000	0.061

Panel B: Regression results

Dep. Var. =	Approval Rate(%)		
	(1)	(2)	(3)
$PeerCPL_{CFPB}(\%)$	0.030	−0.047	−0.145
	(0.275)	(0.323)	(0.225)
$PeerCPL_{CFPB}(\%) \times Post$	0.821**	1.107***	0.842***
	(0.326)	(0.388)	(0.306)
$PeerCPL_{CFPB}(\%) \times Post \times High\ MktShare_{Non-CFPB}$	−1.165**		
	(0.506)		
$PeerCPL_{CFPB}(\%) \times Post \times High\ Sold_{Non-CFPB}$		−0.757*	
		(0.454)	
$PeerCPL_{CFPB}(\%) \times Post \times High\ Bad\ Yelp\ Review_{CFPB}$			−1.035*
			(0.528)
Baseline Controls	Yes	Yes	Yes
Partitioning variable	n.a.	Yes	Yes
Post × Partitioning variable	Yes	Yes	Yes
$PeerCPL_{CFPB}(\%) \times$ Partitioning variable	Yes	Yes	Yes
Bank-county, Bank-year, State-year FE	Yes	Yes	Yes
N (bank-county-years)	44,948	44,948	44,948
Adj. R^2	0.839	0.839	0.839

This table reports the results of analyses conditional on non-CFPB rivals' expertise, incentives, and opportunities. *Approval Rate(%)* is the percentage of the number of mortgage applications that the non-CFPB rival approves in a county-year. *$PeerCPL_{CFPB}(\%)$* is the cumulative number of mortgage complaints in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. *Post* is set to one for 2013−2015 and zero for 2011−2012. *High MktShare_{Non-CFPB}* is an indicator set to one when the market share of a non-CFPB rival in the county in 2012 (*MktShare_{Non-CFPB}*) is above 10%. *High Sold_{Non-CFPB}* is an indicator set to one when the fraction of approved loans that are sold (*Sold_{Non-CFPB}*) is above the sample median. *High Bad Yelp Review_{CFPB}* is an indicator set to one for a county with the proportion of CFPB banks that have at least one Yelp rating ≤3 out of 5 in the county from 2011 to the current year (*Bad Yelp Review_{CFPB}*) above the sample quintile. Panel A provides the descriptive statistics of the partitioning variables. Panel B reports the regression results. Appendix B provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

we compute the fraction of approved mortgage loans that are sold (*Sold*) and create an indicator (*High Sold_{Non-CFPB}*) for bank-county-year with *Sold* above the sample median. Column (2) of Panel B shows the estimation results of Equation (1) augmented with the interaction term $PeerCPL_{CFPB}(\%) \times Post \times High\ Sold_{Non-CFPB}$. We find a significantly negative coefficient on this interaction term, as predicted.

Next, we examine the role of alternative information on CFPB banks' local operations. Intuitively, the complaint disclosures are more useful to rivals when there is less alternative information. Rivals can gather local information from word-of-mouth, online reviews, customer surveys, and social interactions with competitors' employees. Our proxy for alternative information is based on the availability of consumer complaints on Yelp, one of the leading platforms for online reviews. We scrape all historical Yelp reviews for each bank operating in the U.S. and manually match the review data with our sample banks.[16] We find that Yelp covers 77% of CFPB banks during our sample period. An average CFPB bank covered by Yelp has 6.63 reviews, including 4.11 bad reviews (i.e., rating ≤3 out of 5) in a county-year. We consider these bad Yelp reviews as consumer complaints against peer banks on Yelp. For each county-year, we compute the fraction of CFPB banks that have at least one bad Yelp review from 2011 to the year (*Bad Yelp Review*), and create an indicator, *High Bad Yelp Review_{CFPB}*, for county-years with *Bad Yelp Review* above the top quintile. Column (3) of Panel B shows that the coefficient on $PeerCPL_{CFPB}(\%) \times Post \times High$ *Bad Yelp Review_{CFPB}* is negative and significant at the 10% level. It suggests that the learning from the complaint disclosures is mitigated when a sufficiently high number of peer banks in the same county receive bad Yelp reviews.[17]

---

[16] We first use the Yelp Fushion API to obtain the business information (i.e., name, location, Yelp page) of all banks in each U.S. city, resulting in 56,976 entities as of May 2022. We then manually match Yelp entity names with HMDA bank names, resulting in 18,376 Yelp businesses covering 3,797 unique bank-counties. For each Yelp entity, we use Python to scrape its historical reviews, including the rating, the date, and the content of reviews. The initial search returns 128,413 reviews for CFPB banks from 2004 (the establishment year of Yelp) to May 2022.

[17] By contrast, the coefficient on *$PeerCPL_{CFPB}(\%) \times Post \times High\ Bad\ Yelp\ Review_{CFPB}$* is statistically insignificant if we partition the sample based on the sample median, suggesting that the learning effect is mitigated only when the bad Yelp reviews are sufficiently prevalent. This may be due to sizable noise in this alternative information. For example, unlike the CFPB, Yelp does not confirm the commercial relationship between a consumer and a bank before posting the review. Also, the reviews may not be about mortgages.

ARTICLE IN PRESS

Y. Dou, M. Hung, G. She et al.   Journal of Accounting and Economics xxx (xxxx) xxx

Overall, the results in Table 4 suggest that expert rivals rely less on the disclosure of complaints against CFPB banks. Rivals with more mortgages that are sold are also less responsive to the complaint disclosures. They respond more when there is less alternative information on CFPB banks.

4.3. Peer complaint disclosure and mortgage approvals across complaint types

In this section, we investigate the types of mortgage complaints to better understand the nature of information learned by non-CFPB rivals. First, following Dou and Roh (2023), we classify a complaint as severe if a bank provides monetary or non-monetary relief to the complainers or if the consumer disputes the bank's response (e.g., Examples 1, 2, and 4 in Appendix A), and the rest as non-severe (e.g., Example 3). More severe complaints increase the likelihood of applicants switching due to poor service of CFPB banks and thus alleviate non-CFPB rivals' adverse selection concerns. In an average county-year, 25.9% of complaints are severe. We then estimate Equation (1) after decomposing $PeerCPL_{CFPB}(\%)$ into two components: severe complaints against CFPB banks, $PeerCPL_{CFPB}(\%)\_Severity$, and non-severe complaints, $PeerCPL_{CFPB}(\%)\_Non\text{-}Severity$. Table 5 Panel A reports descriptive statistics of the two components. In column (1) of Panel B, we find that the coefficient on $PeerCPL_{CFPB}(\%)\_Severity \times Post$ is positive and significant at the 10% level, while the coefficient on $PeerCPL_{CFPB}(\%)\_Non\text{-}Severity \times Post$ is insignificant at conventional levels. The results suggest that the learning effect concentrates primarily on severe complaints, which are more likely to reveal peer banks' poor service quality.

Second, we classify complaints based on whether they are related to loan underwriting practices. Underwriting issues are directly linked to banks' screening ability and thus more relevant to rivals' adverse selection concerns. In an average county-year, 12.3% of complaints pertain to underwriting issues. We estimate Equation (1) after decomposing $PeerCPL_{CFPB}(\%)$ into $PeerCPL_{CFPB}(\%)\_Underwriting$, which includes complaints with underwriting issues, and $PeerCPL_{CFPB}(\%)\_Non\text{-}Underwriting$,

Table 5
Peer complaint disclosure and mortgage approvals across complaint types.

Panel A: Descriptive statistics on the partitioning variable (N = 44,948)					
Variable	Mean	Std. dev.	Q1	Median	Q3
$PeerCPL_{CFPB}(\%)\_Severity$	0.130	0.152	0.000	0.100	0.205
$PeerCPL_{CFPB}(\%)\_Non\text{-}Severity$	0.229	0.262	0.000	0.173	0.343
$PeerCPL_{CFPB}(\%)\_Underwriting$	0.048	0.064	0.000	0.023	0.080
$PeerCPL_{CFPB}(\%)\_Non\text{-}Underwriting$	0.312	0.346	0.000	0.238	0.464

Panel B: Analysis across different types of complaints		
Dep. Var. =	Approval Rate(%)	
	(1)	(2)
$PeerCPL_{CFPB}(\%)\_Severity$	0.135	
	(0.446)	
$PeerCPL_{CFPB}(\%)\_Non\text{-}Severity$	−0.026	
	(0.310)	
$PeerCPL_{CFPB}(\%)\_Severity \times Post$	1.211*	
	(0.724)	
$PeerCPL_{CFPB}(\%)\_Non\text{-}Severity \times Post$	0.482	
	(0.468)	
$PeerCPL_{CFPB}(\%)\_Underwriting$		−0.474
		(0.989)
$PeerCPL_{CFPB}(\%)\_Non\text{-}Underwriting$		0.009
		(0.245)
$PeerCPL_{CFPB}(\%)\_Underwriting \times Post$		3.052*
		(1.631)
$PeerCPL_{CFPB}(\%)\_Non\text{-}Underwriting \times Post$		0.446
		(0.351)
Baseline Controls	Yes	Yes
Bank-county, Bank-year, State-year FE	Yes	Yes
N (bank-county-years)	44,948	44,948
Adj. R^2	0.839	0.839

This table reports the effect of disclosing different types of peer consumer complaints on mortgage approval rates. *Approval Rate(%)* is the percentage of the number of mortgage applications that the non-CFPB rival approves in a county-year. *Post* is set to one for 2013−2015 and zero for 2011−2012. $PeerCPL_{CFPB}(\%)\_Severity$ is the cumulative number of mortgage complaints with relief or consumer dispute in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. $PeerCPL_{CFPB}(\%)\_Non\text{-}Severity$ is $PeerCPL_{CFPB}(\%)$ minus $PeerCPL_{CFPB}(\%)\_Severity$. $PeerCPL_{CFPB}(\%)\_Underwriting$ is the cumulative number of underwriting-related mortgage complaints in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. $PeerCPL_{CFPB}(\%)\_Non\text{-}Underwriting$ is $PeerCPL_{CFPB}(\%)$ minus $PeerCPL_{CFPB}(\%)\_Underwriting$. Panel A provides the descriptive statistics. Panel B reports the regression results. Appendix B provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

which relates to other complaints. Column (2) of Panel B shows that $PeerCPL_{CFPB}(\%)\_Underwriting \times Post$ loads positively and significantly at the 10% level, whereas $PeerCPL_{CFPB}(\%)\_Non\text{-}Underwriting \times Post$ does not load at conventional levels. The results suggest that the learning effect concentrates on complaints about loan underwriting of CFPB banks, which are more informative about their screening ability.

4.4. An alternative explanation

An alternative explanation for our findings is that non-CFPB rivals increase approval rates due to improved creditworthiness of their applicant pool, in the absence of learning CFPB banks' operational deficiencies. This increase may arise from consumers migrating from CFPB banks to non-CFPB rivals after the former withdraw from the markets or consumers see more complaints against the former. As long as the borrowers migrating to non-CFPB rivals are more creditworthy than their existing applicants, the credit quality of their applicant pool improves. Note that we have already controlled for a battery of variables that capture loan risk (e.g., applicant income and loan-to-income ratios).[18] In an untabulated test, we replace *Approval Rate(%)* with *Applicant Income* and *Loan to Income* as alternative dependent variables and drop these two as explanatory variables in Equation (1). We do not observe a significant increase (decrease) in *Applicant Income* (*Loan to Income*) for non-CFPB rivals in counties with higher $PeerCPL_{CFPB}(\%)$ after the complaint disclosure. Nevertheless, we conduct two sets of analyses to rule out this explanation.

4.4.1. CFPB banks' pullback

One source of the potentially improved creditworthiness of applicants is that CFPB banks pull back from the markets with more consumer complaints, and the consumers migrating to non-CFPB rivals are generally less risky than the existing customers of non-CFPB rivals. To assess this explanation, we perform three tests and report the results in Panel A of Table 6. First, Fuster et al. (2021) find no change in CFPB banks' total mortgage lending but a change in the composition of lending, as reflected in a decrease (an increase) in the market share of FHA mortgage originations ("jumbo" mortgage originations) of CFPB banks after 2011. In the regression for column (1), we exclude FHA mortgages from the calculation of non-CFPB rivals' approval rates to mitigate the concern of CFPB banks withdrawing from the FHA mortgage market. Second, we compute CFPB banks' market share in each county in 2009 multiplied by 100 to capture their market presence before the adoption of the 2010 Dodd-Frank Act (*CFPB Bank Market Share(%)*). In the regression for column (2), we include the interaction between this variable and *Post* to control for the continuation of CFPB banks' potential pullback around the complaint disclosure.[19] Third, we construct the approval rates and the attributes of received and approved loan applications for CFPB banks at the bank-county-year level. We report the results in column (3) after including these variables that capture CFPB banks' reactions. We find that the coefficient on $PeerCPL_{CFPB}(\%) \times Post$ remains significantly positive in all columns. Thus, our results are unlikely to be driven by CFPB banks' pullback from the local mortgage market after the complaint disclosure.

4.4.2. Consumers' reactions to complaint disclosures

Another source of applicants' potentially increased creditworthiness is that borrowers learn from the complaint database that CFPB banks have low-quality mortgage products/services and therefore migrate to non-CFPB rivals. If consumers' reactions drive our findings, we should observe a larger effect of the complaint disclosure on non-CFPB rivals' approval rates in areas where consumers are more likely to use the disclosures or are more sophisticated.

To measure consumers' usage of the disclosures, we use the state-level Google Search Volume Index (SVI) for the keyword "CFPB" in that year. A higher index indicates that consumers spend more effort acquiring information from the complaint database. We construct an indicator variable, *High Google SVI*, which equals one for counties in states with above-median SVI, and zero otherwise. We add the interaction term $PeerCPL_{CFPB}(\%) \times Post \times High\ Google\ SVI$ to Equation (1) and report the results in Table 6, Panel B.[20] We do not find a significant coefficient on $PeerCPL_{CFPB}(\%) \times Post \times High\ Google\ SVI$. The result suggests that the documented effect does not vary with consumers' information acquisition from the database.

Next, we posit that sophisticated consumers are better able to process information from the database. We use the proportion of populations with a high school diploma (*Education*) in a county to proxy for consumer sophistication (Gurun et al., 2016). Our indicator variable, *High Education*, equals one for counties with above-median *Education*, and zero otherwise. We add the interaction term $PeerCPL_{CFPB}(\%) \times Post \times High\ Education$ to Equation (1).[21] As shown in Panel B of Table 6, the coefficient on this interaction is insignificant at conventional levels. Overall, these results suggest that the documented effect is unlikely to be driven by consumers' reactions alone.[22]

---

[18] If we add quadratic and cubic terms of *Applicant Income* and *Loan-to-Income* and interact each of the two variables with the other nine control variables, our inference is unchanged (untabulated).

[19] The main effect of *CFPB Bank Market Share(%)* is absorbed by the bank-county fixed effects.

[20] The effects of *High Google SVI* and *Post* × *High Google SVI* are absorbed by state-year fixed effects.

[21] The main effect of *High Education* is absorbed by bank-county fixed effects.

[22] We cannot fully rule out this alternative explanation as the two measures may be noisy and thus urge caution in interpreting these results.

Table 6
Alternative explanations.

Panel A: Pullback of CFPB banks

Dep. Var. =	Approval Rate(%)		
	Exclude FHA loans	Control for CFPB banks' market share	Control for CFPB banks' reactions
	(1)	(2)	(3)
$PeerCPL_{CFPB}(\%)$	−0.037	−0.043	−0.046
	(-0.238)	(0.221)	(0.220)
$PeerCPL_{CFPB}(\%) \times Post$	0.833***	0.545**	0.676**
	(0.284)	(0.275)	(0.270)
CFPB Bank Market Share(%) × Post		0.012**	
		(0.005)	
CFPB Banks' Average Approval Rate			
Approval Rate(%) (CFPB Banks)			−0.007
			(0.010)
CFPB Banks' Received Loan Application Attributes			
Applicant Income (CFPB Banks)			−0.286
			(0.463)
Loan to Income (CFPB Banks)			−0.078
			(0.246)
Gender (CFPB Banks)			0.300
			(0.672)
Race (CFPB Banks)			−1.127
			(1.142)
Not Secured (CFPB Banks)			−2.791
			(1.928)
Loan Type (CFPB Banks)			0.281
			(1.478)
Property Type (CFPB Banks)			3.637*
			(1.921)
CFPB Banks' Approved Loan Application Attributes			
Applicant Income (CFPB Banks)			0.141
			(0.256)
Loan to Income (CFPB Banks)			0.039
			(0.284)
Gender (CFPB Banks)			2.102*
			(1.146)
Race (CFPB Banks)			−0.587
			(1.145)
Not Secured (CFPB Banks)			−1.032
			(2.442)
Loan Type (CFPB Banks)			0.890
			(1.388)
Property Type (CFPB Banks)			−2.199
			(1.744)
Baseline Controls	Yes	Yes	Yes
Bank-county, Bank-year, State-year FE	Yes	Yes	Yes
N (bank-county-years)	42,035	44,948	44,948
Adj. R²	0.836	0.839	0.839

Panel B: Analysis conditional on consumers' use of disclosure and sophistication

Dep. Var. =	Approval Rate(%)	
	(1)	(2)
$PeerCPL_{CFPB}(\%)$	0.072	0.036
	(0.327)	(0.283)
$PeerCPL_{CFPB}(\%) \times Post$	0.703*	0.911**
	(0.403)	(0.356)
$PeerCPL_{CFPB}(\%) \times Post \times High\ Google\ SVI$	0.015	
	(0.514)	
$PeerCPL_{CFPB}(\%) \times Post \times High\ Education$		−0.458
		(0.410)
Baseline Controls	Yes	Yes
Partitioning variable	n.a.	n.a.
Post × Partitioning variable	n.a.	Yes
$PeerCPL_{CFPB}(\%) \times$ Partitioning variable	Yes	Yes
Bank-county, Bank-year, State-year FE	Yes	Yes
N (bank-county-years)	44,948	44,948
Adj. R²	0.839	0.839

Panel A reports the results of analyses related to CFPB banks' pullback from the local mortgage markets. Column (1) uses the approval rates of non-FHA mortgages loans, the percentage of the number of non-FHA mortgage applications that the non-CFPB rival approves in a county-year, as the dependent variable. In columns (2) and (3), the dependent variable, *Approval Rate(%)*, is the percentage of the number of mortgage applications that the non-CFPB rival approves in a county-year. *PeerCPL$_{CFPB}$(%)* is the cumulative number of mortgage complaints in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. *Post* is set to one for 2013−2015 and zero for 2011−2012. Column (2) includes the interaction term between *CFPB Bank Market Share(%)*, the market share of CFPB banks in the county in 2009 multiplied by 100, and *Post*. Column (3) controls for the approval rates and the attributes of received and approved loan applications for CFPB banks. For each county-year, we take the average of approval rates across all CFPB banks, weighted by the number of applications. We also take the average of attributes of received and approved loan applications for CFPB banks within each county-year. Panel B reports the results of analyses related to consumers' reactions. *High Google SVI* is an indicator set to one for counties in states with the state-level Google Search Volume Index (*SVI*) for the keyword "CFPB" (*Google SVI*) above the sample median. *High Education* is an indicator set to one for counties with the proportion of the population in a county with a high school degree in 2012 (*Education*) above the sample median. Appendix 3 provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

4.5. Robustness checks

4.5.1. Alternative samples

In the sample selection, we eliminated players that were only marginally involved in mortgage lending in a local market by requiring at least 40 loan applications for a bank-county-year observation. We check the sensitivity of our results to using two alternative cutoffs, with the results reported in columns (1) and (2) of Table 7, Panel A. We continue to find robust results when requiring at least 20 and 60 loan applications for a bank-county-year, respectively.[23]

Our primary tests focus on the responses by non-CFPB rivals partly because they are not covered by the complaint database and thus enable us to better identify the learning-from-peer effect. However, this design may be compromised if these banks are covered by another customer review platform such as Yelp. To mitigate this concern, we scrape all Yelp reviews of non-CFPB rivals. Yelp covers only about 25% of them and 5% of bank-county-years in our sample. An average bank-county-year covered by Yelp has 1.86 reviews, including 0.89 bad reviews. Given the paucity of Yelp reviews on non-CFPB rivals, we do not expect these reviews to compromise the identification of the learning-from-peer effect. Consistent with this expectation, we find that our inference remains robust after removing observations with bad Yelp reviews from the sample (column (3) of Table 7, Panel A).

To address the concern that our findings are driven by time-varying local economic conditions that are correlated with both the intensity of consumer complaints and non-CFPB rivals' lending decisions, we control for state-year fixed effects in all the regressions. We further address this issue by examining banks in contiguous counties, where the economic conditions typically are similar. We first sort counties into deciles according to the intensity of consumer complaints as of the disclosure date (March 28, 2013). We define counties with the most complaints (i.e., the intensity of complaints is in the top decile) as treatment counties. Next, for each treatment county, we select control group counties that do not have complaints against CFPB banks and are adjacent to the treatment county.[24] If a treatment county has multiple matched counties, we choose the one with the *Market Size* closest to the treatment county. We focus on banks located in these contiguous counties. These banks share similar exposure to economic conditions, but only one of the counties has intensive consumer complaints. We then estimate Equation (1) using this matched sample and report the results in column (4) of Table 7, Panel A. The coefficient on *PeerCPL$_{CFPB}$(%) × Post* continues to be significantly positive, suggesting that unobservable local economic conditions are unlikely to explain our findings.

4.5.2. Alternative measures

Throughout the analyses, we scale the number of mortgage complaints by the number of CFPB banks' mortgage originations in the same county to control for the size of these banks' local operations. We rerun our analysis after replacing *PeerCPL$_{CFPB}$(%)* with the quintile rank (*PeerCPL$_{CFPB}$_Rank*) of the number of (unscaled) consumer complaints in the county. As reported in column (1) of Table 7, Panel B, our inference remains unchanged.

We use the cumulative number of complaints from 2011 to the current year to construct our main test variable. To assess the robustness of our results to this choice, we construct three alternative measures of complaint intensity. The first two are *PeerCPL$_{CFPB}$_2yrs(%)*, using a two-year moving window, and *PeerCPL$_{CFPB}$_3yrs(%)*, using a three-year moving window. As reported in columns (2) and (3) of Table 7, Panel B, our results are robust to using these two measures. The third is a time-invariant measure *PeerCPL$_{CFPB}$_PreDisc(%)*, which is the intensity of mortgage complaints against peer banks as of the disclosure date, March 28, 2013. By construction, this measure is unaffected by CFPB banks' response to the complaint disclosure. As reported in column (4) of Table 7, Panel B, the coefficient on *PeerCPL$_{CFPB}$_PreDisc(%) × Post* is positive and

---

[23] For a bank-county-year in our sample (with at least 40 applications), the bank may view neighboring counties without sufficient applications as plausible markets to expand credit supply. Naturally, the approval rates in these counties are economically less important. Nevertheless, we add bank-county-years for these counties to our sample and estimate Equation (1) using weighted least squares with the number of applications as the weight. Our inferences remain unchanged (untabulated).

[24] We obtain adjacent county data from the National Bureau of Economic Research (https://www.nber.org/data/county-adjacency.html).

ARTICLE IN PRESS

Y. Dou, M. Hung, G. She et al.   Journal of Accounting and Economics xxx (xxxx) xxx

Table 7
Robustness checks.

Panel A: Alternative samples

Dep. Var. =	Approval Rate(%)			
	#App ≥20	#App ≥60	Without bad Yelp reviews	Adjacent counties
	(1)	(2)	(3)	(4)
$PeerCPL_{CFPB}(\%)$	−0.042	0.014	−0.107	−0.565
	(0.200)	(0.230)	(0.218)	(1.177)
$PeerCPL_{CFPB}(\%)\times Post$	0.486**	0.584**	0.672**	1.886**
	(0.225)	(0.287)	(0.274)	(0.802)
Baseline Controls	Yes	Yes	Yes	Yes
Bank-county, Bank-year, State-year FE	Yes	Yes	Yes	Yes
Pair-year FE	No	No	No	Yes
N (bank-county-years)	70,472	31,998	43,561	11,653
Adj. R^2	0.795	0.872	0.839	0.869

Panel B: Alternative measures

Dep. Var. =	Approval Rate(%)				Approval Rate(%) $_{t+1}$
	(1)	(2)	(3)	(4)	(5)
PeerCPL$_{CFPB}$_Rank	0.074				
	(0.079)				
PeerCPL$_{CFPB}$_Rank × Post	0.185**				
	(0.072)				
PeerCPL$_{CFPB}$_2yrs (%)		−0.156			
		(0.199)			
PeerCPL$_{CFPB}$_2yrs (%) × Post		0.602**			
		(0.234)			
PeerCPL$_{CFPB}$_3yrs (%)			−0.119		
			(0.211)		
PeerCPL$_{CFPB}$_3yrs (%) × Post			0.673***		
			(0.257)		
PeerCPL$_{CFPB}$_PreDisc (%) × Post				0.434***	
				(0.168)	
PeerCPL$_{CFPB}$(%)					−0.298
					(0.235)
PeerCPL$_{CFPB}$(%) × Post					0.694***
					(0.247)
Baseline Controls	Yes	Yes	Yes	Yes	Yes
Bank-county, Bank-year, State-year FE	Yes	Yes	Yes	Yes	Yes
N (bank-county-years)	44,948	44,948	44,948	44,948	44,461
Adj. R^2	0.839	0.839	0.839	0.839	0.834

This table reports the effect of disclosing peer consumer complaints on mortgage approval rates using alternative samples and specifications. Panel A reports the results using two alternative cutoffs for the sample construction, removing bank-county-years with at least one Yelp rating ≤3 out of 5, and an alternative sample with adjacent counties. The dependent variable, *Approval Rate(%)*, is the percentage of the number of mortgage applications that the non-CFPB rival approves in a county-year. *PeerCPL$_{CFPB}$* is the cumulative number of mortgage complaints in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. *Post* is set to one for 2013−2015 and zero for 2011−2012. Panel B reports the results using alternative measures of peer consumer complaints and approval rates. *PeerCPL_Rank* is the quintile rank of the number of mortgage complaints (unscaled) in a county against CFPB banks as of the disclosure date. *PeerCPL$_{CFPB}$_2yrs(%)* and *PeerCPL$_{CFPB}$_3yrs(%)* are the cumulative number of mortgage complaints in a county against CFPB banks from year *t*-1 and *t*-2 to year *t*, respectively, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. *PeerCPL$_{CFPB}$_PreDisc(%)* is the total number of mortgage complaints as of the disclosure date in a county against CFPB banks, scaled by the number of mortgage originations by these banks in the county in 2011, multiplied by 100. Approval Rate(%) $_{t+1}$ is the approval rates in the next year. Appendix B provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

significant at the 1% level, consistent with the notion that rival banks increase approval rates in markets with more intensive complaints against CFPB banks following the disclosure.[25]

Finally, the learning literature typically examines how peer information in the current period influences firms' actions in the next period to ensure that such information (e.g., in annual financial reports) is publicly available to the firms (Roychowdhury et al., 2019; Darmouni and Sutherland, 2021). Since the complaint database is updated on a daily basis after the disclosure date, using the current approval rates allows rival banks to base their decisions on up-to-date information in the database. Nevertheless, we replace the current approval rate with the next year's approval rate as the dependent variable and continue to find consistent results, as shown in column (5) of Table 7, Panel B.

---

[25] The main effect of *PeerCPL$_{CFPB}$_PreDisc(%)* is absorbed by bank-county fixed effects.

ARTICLE IN PRESS

Y. Dou, M. Hung, G. She et al.　　　　　　　　　　　　　　　　　　　　　　　Journal of Accounting and Economics xxx (xxxx) xxx

5. Additional analyses

5.1. Other bank actions in response to peer consumer complaints

To support the expansion of mortgage lending in local markets, non-CFPB rivals might undertake other actions in addition to increasing approval rates. We investigate two actions: expansions of branch networks and workforce. First, we investigate whether rival banks increase the number of bank branches in a local market. We collect information about the locations of all bank branches in the U.S. from the Summary of Deposits data (SOD) provided by the Federal Deposit Insurance Corporation (FDIC), and count the number of branches a bank has in each county-year (#Branches). We include all bank-county-years that have at least one mortgage application from the HMDA database and report the descriptive statistics in Panel A of Table 8.[26] An average bank-county-year in this sample (N = 501,651) has 0.354 branches. Columns (1) and (2) of Panel B report the estimation results of Equation (1) using #Branches as the dependent variable. As the dependent variable is a count variable, we estimate Equation (1) using a fixed-effects Poisson model (Cohn et al., 2022). We find that $PeerCPL_{CFPB}(\%) \times Post$ loads positively and significantly at the 1% level in both columns, suggesting that non-CFPB rivals increase the number of branches in local markets with more intensive mortgage complaints against CFPB banks following the disclosure. In terms of economic significance, an interquartile increase in $PeerCPL_{CFPB}(\%)$ raises the number of branches by 35.6% (2.8%/7.9%), relative to the average within-bank-county standard deviation.[27]

Second, we examine whether rival banks are more likely to recruit employees to meet the increased workload associated with credit expansion. We obtain information about job postings from the Burning Glass database, which collects the near universe of U.S. job vacancies posted online since 2007. We match the job postings with our sample based on the name of recruiting company and the Zip Code of the job location. We create an indicator, New Hiring, for bank-county-years with at least one job posting. We include all bank-county-years with at least one mortgage application from the HMDA database. We also exclude banks not covered by Burning Glass, although our results are not sensitive to this exclusion (untabulated). As reported in Panel A of Table 8, 4.1% of bank-county-years have online job postings. Columns (3) and (4) of Panel B report the estimation of Equation (1) using New Hiring as the dependent variable. The coefficient on $PeerCPL_{CFPB}(\%) \times Post$ is 0.009 and significant at the 1% level. The results suggest that non-CFPB rivals are more likely to have a new job posting in markets with more intensive mortgage complaints against the CFPB banks after the disclosure. Relative to the within-bank-county standard deviation (0.032), an interquartile increase in $PeerCPL_{CFPB}(\%)$ raises the likelihood of job posting by 13.5% (=0.009×0.480/ 0.032).

5.2. Implications on non-CFPB rivals' profitability

To assess the implications on non-CFPB rivals' overall performance, we examine their profitability. The complaint disclosure alleviates adverse selection concerns of non-CFPB rivals and helps them identify areas with more new profitable opportunities, which were pooled with other areas and thus not obvious prior to the disclosure. As such, the new clients and branches that they are taking on should improve their profitability. We construct a sample of 12,309 non-CFPB bank-year observations from 2011 to 2015 and estimate the following model:[28]

$$ROE / ROA_{i,t+1} = \beta_1 PeerCPL_{CFPB}\_Agg(\%)_{i,t} + \beta_2 PeerCPL_{CFPB}\_Agg(\%)_{i,t} \times Post_t + Controls + \nu_i + \eta_t + \varepsilon_{i,t}, \qquad (2)$$

where i denotes non-CFPB banks, and t denotes years. The bank-year-level $PeerCPL_{CFPB}\_Agg(\%)$ is the average of the county-level $PeerCPL_{CFPB}(\%)$ across all counties, weighted by the number of loan originations by bank i in each county-year. The indicator Post is set to one for years during and after the release of the mortgage complaint data (i.e., 2013−2015), and zero otherwise. Following Loutskina and Strahan (2011), we control for a host of bank characteristics: bank size (Size), trading securities (Securities), interest expenses on deposits (Deposit Rate), total deposits (Deposit), real estate loans (Real Estate Loans), commercial and industrial loans (C&I Loans), unused loan commitments (Unused Commitment), and letters of credit (Letters of Credit).

Panel A of Table 9 reports the descriptive statistics for these variables. Panel B shows that the coefficient on Peer-$CPL_{CFPB}\_Agg(\%) \times Post$ is significantly positive for both specifications. This result suggests that non-CFPB rivals experience

---

[26]　We do not restrict the sample to bank-county-years with at least 40 applicants for the analyses of branch networks and hiring. The results (untabulated) are robust if we apply this sample restriction.

[27]　Specifically, in this Poisson model, an interquartile increase in $PeerCPL_{CFPB}(\%)$ is associated with a 2.8% increase in the number of branches, where 2.8% is calculated as $0.480 \times (e^{0.057}-1)$. Since the effect is expressed on a percentage change basis, we obtain the average within-bank-county standard deviation (7.9%) by computing the standard deviation of the annual percentage change in the number of branches for each bank-county and taking the average across all bank-counties. Since an average county-year in the sample has 28.9 branches of non-CFPB rivals, the 2.8% increase in the number of branches also translates into 0.81 (2.8% × 28.9) more branches.

[28]　We use a bank-year sample for this test because disaggregated financial information on a bank-county-year is not publicly available. The number of observations is slightly smaller than the number of bank-years in Panel B of Table 1 due to the additional data requirement on future ROA or ROE.

Table 8
Branches and new hires.

Panel A: Summary statistics

Variable	N	Mean	Std. dev.	Q1	Median	Q3
#Branches	501,651	0.354	1.420	0.000	0.000	0.000
New Hiring	396,318	0.041	0.199	0.000	0.000	0.000
PeerCPL_CFPB(%)	501,651	0.301	0.383	0.000	0.185	0.480
Post	501,651	0.603	0.489	0.000	1.000	1.000
Applicant Income	501,651	4.514	0.644	4.111	4.466	4.868
Loan to Income	501,651	1.956	1.079	1.201	1.864	2.548
Gender	501,651	0.231	0.316	0.000	0.077	0.333
Race	501,651	0.854	0.261	0.800	1.000	1.000
Not Secured	501,651	0.028	0.131	0.000	0.000	0.000
Loan Type	501,651	0.801	0.342	0.714	1.000	1.000
Property Type	501,651	0.939	0.201	1.000	1.000	1.000
Branch Presence	501,651	0.128	0.335	0.000	0.000	0.000
Market Size	501,651	12.490	1.945	11.044	12.481	13.954
Income Growth(%)	501,651	3.628	3.405	1.653	3.561	5.294
Unemployment(%)	501,651	7.144	2.577	5.300	6.864	8.700

Panel B: Regression results

Dep. Var. =	#Branches		New Hiring	
	(1)	(2)	(3)	(4)
PeerCPL_CFPB(%)	−0.007	−0.012	−0.004	−0.004
	(0.009)	(0.008)	(0.002)	(0.002)
PeerCPL_CFPB(%)× Post	0.051***	0.057***	0.009***	0.009***
	(0.012)	(0.011)	(0.003)	(0.003)
Applicant Income		−0.037***		0.000
		(0.008)		(0.001)
Loan to Income		−0.003		0.000
		(0.004)		(0.000)
Gender		−0.007		0.001
		(0.013)		(0.001)
Race		−0.035**		−0.001
		(0.015)		(0.001)
Not Secured		0.047**		0.001
		(0.023)		(0.003)
Loan Type		0.086***		0.000
		(0.032)		(0.001)
Property Type		0.040*		0.001
		(0.022)		(0.003)
Branch Presence		0.594***		0.081***
		(0.017)		(0.007)
Market Size		0.069***		0.005*
		(0.013)		(0.003)
Income Growth(%)		−0.000		0.000**
		(0.000)		(0.000)
Unemployment(%)		0.000		0.000
		(0.003)		(0.001)
Bank-county FE	Yes	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes	Yes
N (bank-county-years)	501,651	501,651	396,318	396,318
Adj./Pseudo R²	0.451	0.452	0.580	0.581

This table reports the effect of disclosing peer consumer complaints on branch opening and new hiring for a non-CFPB rival in counties in which it receives at least one mortgage application. *#Branches* is the number of branches of the non-CFPB rival in a county-year. *New Hiring* is an indicator for bank-county-years with new online job posting. *PeerCPL_CFPB(%)* is the cumulative number of mortgage complaints in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. *Post* is set to one for 2013−2015 and zero for 2011−2012. Panel A reports the descriptive statistics. Panel B reports the regression results. Columns (1) and (2) report the Poisson regression estimates, columns (3) and (4) report the linear probability regression estimates. Appendix B provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

greater improvements in profitability after the disclosure when CFPB banks face more intensive mortgage complaints. In terms of economic significance, an interquartile increase in *PeerCPL_CFPB_Agg(%)* increases ROE by 0.30% (=0.009×0.341) and

Table 9
Profitability of non-CFPB rivals.

Panel A: Summary statistics						
Variable	N	Mean	Std. dev.	Q1	Median	Q3
ROE	12,309	0.087	0.069	0.052	0.083	0.119
ROA	12,309	0.009	0.007	0.006	0.009	0.012
PeerCPL$_{CFPB}$_Agg(%)	12,309	0.338	0.295	0.127	0.279	0.468
Size	12,309	12.894	1.040	12.151	12.769	13.519
Securities	12,309	0.087	0.087	0.015	0.064	0.130
Deposit Rate	12,309	0.007	0.004	0.004	0.007	0.010
Deposit	12,309	0.838	0.064	0.805	0.849	0.883
Real Estate Loans	12,309	0.532	0.142	0.435	0.534	0.632
C&I Loans	12,309	0.076	0.060	0.034	0.063	0.105
Unused Commitment	12,309	0.105	0.061	0.060	0.095	0.138
Letters of Credit	12,309	0.003	0.004	0.000	0.002	0.004

Panel B: Regression analysis			
Dep. Var. =		ROE$_{t+1}$	ROA$_{t+1}$
		(1)	(2)
PeerCPL$_{CFPB}$_Agg(%)		0.007	0.001
		(0.005)	(0.000)
PeerCPL$_{CFPB}$_Agg(%) × Post		0.009**	0.001**
		(0.005)	(0.000)
Size		−0.037***	−0.005***
		(0.007)	(0.001)
Securities		0.066***	0.006***
		(0.025)	(0.002)
Deposit Rate		−2.838***	−0.357***
		(0.560)	(0.052)
Deposit		0.072***	0.003
		(0.022)	(0.002)
Real Estate Loans		0.032	0.004**
		(0.021)	(0.002)
C&I Loans		0.003	0.001
		(0.037)	(0.003)
Unused Commitment		0.087***	0.010***
		(0.030)	(0.003)
Letters of Credit		−0.323	−0.022
		(0.315)	(0.028)
Bank FE		Yes	Yes
Year FE		Yes	Yes
N (bank-years)		12,309	12,309
Adj. R^2		0.627	0.674

Panel A reports descriptive statistics for non-CFPB rivals from 2011 to 2015. Panel B reports the effect of consumer complaint disclosure on profitability of non-CFPB rivals. *ROE* is net income scaled by the book value of equity. *ROA* is net income scaled by total assets. *PeerCPL$_{CFPB}$_Agg(%)* is the average of the county-level *PeerCPL$_{CFPB}$(%)* across all counties, weighted by the number of loan originations by a bank in each county. *Post* is set to one for 2013−2015 and zero for 2011−2012. Appendix B provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

ROA by 0.03% (=0.001×0.341) after the disclosure.[29] The findings are consistent with non-CFPB rivals benefiting from learning the weaknesses of the CFPB banks.

5.3. Analysis of CFPB banks with few complaints

Throughout the paper, we focus on the responses of the non-CFPB rivals because they provide a relatively clean sample to test the learning channel. For example, the association between a CFPB bank's lending changes and complaints against another CFPB bank can be driven by the CFPB's more stringent monitoring in areas with more complaints. To the extent that

---

[29] Without a structural model, it is difficult to assess the plausibility of the improved ROE and ROA (0.30% and 0.03%). Nevertheless, we compare them to the documented increase in approval rates (0.38%) in Table 3. For a one unit increase in approval rate, non-CFPB rivals' ROE and ROA increase by 0.789 (=0. 30%/0.38%) and 0.079 (=0.03%/0.38%), respectively. Loutskina and Strahan (2011) argue that investing in private information, as proxied by geographic loan concentration, helps lenders overcome adverse selection in mortgage markets. They find that moving from fully diversified lenders (HHI = 0) to fully concentrated lenders (HHI = 1) would raise mortgage approval rate by 3.77% (Table 3 column 1), annualized ROE by 3% (Table 6 column 3), and annualized ROA by 0.3% (Table 6 column 1). In other words, for a one unit increase in approval rate, their sample banks' ROE and ROA increase by 0.796 (=3%/3.77%) and 0.080 (=0.3%/3.77%), respectively. The similarity between their numbers and ours suggest that the economic significance of non-CFPB rivals' improved profitability is sensible.

regulators of non-CFPB rivals do not follow suit, these banks are less prone to this problem (Manski, 1993). Nevertheless, we acknowledge that our argument for learning-from-peers applies to CFPB banks as well and extend our main analyses to these banks. The analysis of CFPB rivals also helps us assess the generalizability of our findings about non-CFPB rivals. We focus the analyses on CFPB banks with few complaints (CFPB rivals) to better disentangle the learning-from-peer effect. It is difficult to do so for CFPB banks with many complaints since these complaints may prevent them from taking advantage of peers' weaknesses and may affect their operations by attracting more scrutiny from the CFPB.

We identify CFPB banks with low complaints (below the sample median of 366 complaints at the bank-year level) and construct a sample of bank-county-years without any complaints for these banks. For the approval rate test, we require at least 40 mortgage applications for each bank-county-year observation, whereas no such requirement is imposed for the branching and hiring tests. We describe the sample selection in Panel A of Table 10. We then estimate the following difference-in-differences specification:

$$Outcome_{i,c,t} = \beta_1 PeerCPL_{Other}(\%)_{i,c,t} + \beta_2 PeerCPL_{Other}(\%)_{i,c,t} \times Post_t + Controls + \nu_{i,c} + \eta_{i,t} + \tau_{s,t} + \varepsilon_{i,c,t}, \tag{3}$$

where $PeerCPL_{Other}(\%)$ is the cumulative number of mortgage complaints in county c against all CFPB banks except for bank i from 2011 to year t, divided by the cumulative number of loan originations by these banks in the same county during the same period, multiplied by 100. In Equation (3), we also include the same controls and fixed effects as in Equation (1).

The results are in Panel B of Table 10. Column (1) presents the results using *Approval Rate(%)* as the outcome variable for CFPB rivals. The coefficient on $PeerCPL_{Other}(\%) \times Post$ is significantly positive, suggesting that these CFPB rivals exhibit a greater increase in approval rates following the complaint disclosure in counties where other CFPB banks receive more intensive complaints. Columns (2) and (3) present the results using the number of branches and new hiring as the outcome variable. We find that CFPB rivals increase the number of branches and the likelihood of posting a job opening in markets with more intensive mortgage complaints against other CFPB banks following the complaint disclosure. Overall, these results suggest that CFPB rivals also learn from the complaint disclosures against other CFPB banks and take advantage of their operational deficiencies.

Table 10
Disclosure of peer consumer complaints and responses by CFPB rivals.

Panel A: Sample selection − CFPB rivals

Selection criteria	# of Loan applications	# of Bank-county -years	# of Banks
Restrict the initial sample to CFPB banks	20,476,150	275,020	126
Require bank-county-year observations to have valid control variables	20,013,538	254,365	119
Restrict to CFPB banks with #complaints below the sample median	7,504,725	154,858	107
Require no complaint for the CFPB rival in the county-year	6,951,269	153,333	107
Sample for the branching test	6,951,269	153,333	107
Sample for the approval rate test (require at least 40 mortgage applications for each bank-county-year)	5,977,778	26,610	97
Sample for the hiring test (require a bank to be covered by Burning Glass)	5,501,615	116,741	74

Panel B: Changes in mortgage approval rates of CFPB rivals with few complaints

Dep. Var. =	Approval Rate(%)	#Branches	New Hiring
	(1)	(2)	(3)
$PeerCPL_{Other}(\%)$	−0.429	0.004	0.001
	(0.263)	(0.009)	(0.003)
$PeerCPL_{Other}(\%) \times Post$	0.698**	0.093***	0.008**
	(0.283)	(0.013)	(0.004)
Baseline Controls	Yes	Yes	Yes
Bank-county FE	Yes	Yes	Yes
Bank-year FE	Yes	Yes	Yes
State-year FE	Yes	Yes	Yes
N (bank-county-years)	26,610	153,333	116,741
Adj./Pseudo R^2	0.844	0.700	0.739

This table reports the effect of disclosing peer consumer complaints on approval rates, branch opening, and new hiring of CFPB rivals with few complaints. *Approval Rate(%)*, is the percentage of the number of mortgage applications that the CFPB rival approves in a county-year. *#Branches* is the number of branches of the CFPB bank in a county-year. *New Hiring* is an indicator for the CFPB rival with a new online job posting in a county-year. *PeerCPL_{Other}(%)* is the cumulative number of mortgage complaints in a county against other CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100. *Post* is set to one for 2013−2015 and zero for 2011−2012. Panel A outlines the sample selection procedure. Panel B reports the regression results. Appendix B provides the variable definitions. Standard errors are clustered by county and reported in parentheses. *, **, and *** denote two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

ARTICLE IN PRESS

Y. Dou, M. Hung, G. She et al.   Journal of Accounting and Economics xxx (xxxx) xxx

6. Conclusion

In this paper, we examine whether and how banks in mortgage markets learn from disaggregated nonfinancial information — consumer complaints — about their peers. We explore a disclosure regulation enacted by the CFPB, which publicly released detailed mortgage complaints against banks under its supervision in 2013. Using 44,948 bank-county-year observations of 3,214 unique non-CFPB rivals from 2011 to 2015, we find robust evidence that these banks increase their mortgage approval rates in counties where CFPB banks receive intensive complaints after the disclosure. The effect is stronger among non-CFPB rivals with less lending experience in the local market, when they are more concerned with credit risk, when there is less alternative information about CFPB banks, and when complaints are more severe and related to screening ability. Moreover, non-CFPB rivals increase the number of branches and the likelihood of posting a job opening in markets with intensive complaints against CFPB banks following the disclosure. Finally, we find similar results for CFPB banks with few complaints, suggesting that they also take advantage of the disclosures about their peers.

Overall, our findings suggest that banks learn from the disclosures about peers' operational deficiencies, particularly bad customer service and weak screening ability, thereby expanding their credit supply. Our evidence supports the learning-from-peers channel through which disclosure regulation can discipline banks by influencing their rivals' expansion decisions. As technology facilitates the compilation and dissemination of the complaint dataset in a timely and reliable manner, such disclosure is likely to be increasingly useful as a policy instrument.

Appendix A. Examples of Mortgage Complaints

Example 1: Complaint against Bank of America

Consumer's state	AZ
Consumer's ZIP	85250
Consumer disputed the response?	No
Issue	Application, originator, mortgage broker
Consumer complaint narrative	We have had a lengthy on-going process with Bank of America local mortgage branch here in XXXX, AZ in attempts to secure financing for our home purchase. To summarize the events that took place with our recent loan process. We began our process with B of A in early XXXX 2015 by obtaining a pre-qualification letter and we began submitting all our documentation … we still did not have the approval we were promised. Given the lack of response from B of A, our seller lost confidence in our ability to obtain financing and would not agree to any closing extension without release of our security deposit of {$17000.00}. Our mortgage contact person, was on a two-week vacation, and with no other covering manager, only an assistant to speak with, we were left with no option other than to ask for a denial from the branch in order to help secure our security funds. During that time and days following, my husband had multiple conversations with staff members at the branch and it appeared that underwriting was having challenges in accurately assessing our income and documents … we lost faith in your company and entertained the option of securing funding. XXXX lenders were able to process, approve and close us in 2 weeks, with no appraisal needed on our XXXX XXXX property. Having familiarized ourselves with the XXXX XXXX XXXX, we feel there has been an absolute breech in processing and failure to deliver on commitments made. Had we not been given multiple promises by the B of A staff to have us closed in an expedited manner, we would have never gone under contract again on this home. We have incurred extensive expenses in this process in excess of {$12000.00}. We have sent numerous letters and to their response was to refund our appraisal of {$420.00}. We do not feel that is acceptable, therefore we are filing complaints with the proper authorities. If needed, we can provide you with copies of the numerous emails that we exchanged between the B of A staff, as well as our realtor. Thank you for your time!
Date complaint sent to company	11/10/2015
Company name	BANK OF AMERICA, NATIONAL ASSOCIATION
Company response to consumer	Closed with monetary relief

Example 2: Complaint against Citizens Financial Group

Consumer's state	NH
Consumer's ZIP	03104
Consumer disputed the response?	Yes
Issue	Credit decision/Underwriting
Consumer complaint narrative	Received pre approval on XX/XX/XXXX. Started full application on XX/XX/XXXX. I was charged {$470.00} for an appraisal on XX/XX/XXXX. As of this evening XX/XX/XXXX the appraisal has not been completed. Citizens bank is claiming that this is due to Dodd Frank and CFPB regulations. I believe this is very misleading and they are trying to blame government regulations on problems with their processes. At this point in the process because of the delays, I do not have the luxury of trying to find another financial institution … This loan needs to close by XX/XX/XXXX or I suffer severe financial consequences due to their negligence. This is by no means credit or income related. Both my wife and I have XXXX Fico scores, over 15 years each on the job, debt and income ratios all well within guidelines. In other words, we are the ones with perfect credit and income for a mortgage loan. We also are putting down about 35% of the purchase price.
Date complaint sent to company	12/4/2015
Company name	CITIZENS FINANCIAL GROUP, INC.
Company response to consumer	Closed with monetary relief

Example 3: Complaint against Ditech Financial LLC

Consumer's state	PA
Consumer's ZIP	19083
Consumer disputed the response?	N/A
Product and sub-product	Conventional fixed mortgage
Issue	Loan servicing, payments, escrow account
Consumer complaint narrative	Ditech Mortgage is calling my work number and my cell phone number at least XXXX times a day, and hanging up (my current payment is within the 15 day grace period allowed).
Date complaint sent to company	12/10/2015
Company name	Ditech Financial LLC
Company response to consumer	Closed with explanation

Example 4: Complaint against U.S. Bancorp

Consumer's state	MA
Consumer's ZIP	01088
Consumer disputed the response?	Yes
Product and sub-product	Conventional fixed mortgage
Issue	Loan modification, collection, foreclosure
Consumer complaint narrative	Hello, We fell behind 3 payments to US Bank XX/XX/2014 shortly after XXXX. It was then suggested that we apply for the "loss mitigation" program to make a payment plan. It has been 18 months with us falling further and further behind and we are not allowed to make any payments even though we could have started paying months ago. They ask for the same paperwork over and over since by the time they send it to the "processor" it's expired. They just told me I need to fill out everything again for the 3rd time and I feel like this is illegal. I just want to pay the mortgage.
Date complaint sent to company	12/29/2015
Company name	U.S. BANCORP
Company response to consumer	Closed with non-monetary relief

Appendix B. Variable definitions

Variable	Definition
Dependent variables	
Approval Rate(%)	The number of approved mortgages divided by the total number of mortgage applications for a bank-county-year, multiplied by 100.
#Branches	The number of a bank's branches in a county-year.
New Hiring	An indicator equal to one for a bank that posts a job opening online in a county-year, and zero otherwise.
Test variables	
Post	An indicator equal to one starting in 2013, and zero otherwise (disclosure date is March 28, 2013).
$PeerCPL_{CFPB}(\%)$	The cumulative number of mortgage complaints in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100.
$PeerCPL_{CFPB}(\%)\_Severity$	The cumulative number of mortgage complaints with (monetary or non-monetary) relief or consumer dispute in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100.
$PeerCPL_{CFPB}(\%)\_Underwriting$	The cumulative number of mortgage complaints with "Application, originator, mortgage broker," "Settlement process and costs," or "Credit decision/underwriting" issues in a county against CFPB banks from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100.
$PeerCPL_{Other}(\%)$	The cumulative number of mortgage complaints in a county against CFPB banks other than the CFPB bank in question from 2011 to the current year, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100.
$PeerCPL_{CFPB}\_Rank$	The quintile rank of the cumulative number of mortgage complaints in a county against CFPB banks from 2011 to the current year.
$PeerCPL_{CFPB}\_2yrs(\%)$	The cumulative number of mortgage complaints in a county against CFPB banks from year t-1 to year t, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100.
$PeerCPL_{CFPB}\_3yrs(\%)$	The cumulative number of mortgage complaints in a county against CFPB banks from year t-2 to year t, scaled by the number of mortgage originations by these banks in the county during the same period, multiplied by 100.
$PeerCPL_{CFPB}\_PreDisc(\%)$	The number of mortgage complaints in a county against CFPB banks as of the disclosure date (March 28, 2013), scaled by the number of mortgage originations by these banks in the county in 2011, multiplied by 100.
Bank-county-year variables	
Applicant Income	The natural logarithm of the average applicant income.
Loan to Income	The average ratio of the loan amount to applicant income.
Gender	The proportion of applications from female applicants.
Race	The proportion of applications from white applicants.
Not Secured	The proportion of applications for mortgages that are not secured by a lien.
Loan Type	The proportion of applications for conventional loans. A conventional loan is a mortgage that is not guaranteed or insured by any government agency, including the Federal Housing Administration (FHA), the Farmers Home Administration (FmHA) and the Department of Veterans Affairs (VA).
Property Type	The proportion of applications for mortgages for one-to-four family housing (as opposed to multifamily housing).
Branch Presence	An indicator equal to one for the presence of a branch of a bank in a county in the previous year, and zero otherwise.
County-year variables	
Market Size	The natural logarithm of the dollar amount of applications in a county in the current year.
Income Growth(%)	Growth rate of income per capita in the previous year, multiplied by 100.
Unemployment(%)	The unemployment rate in a county in the previous year, multiplied by 100.
CFPB Bank Market Share(%)	The number of approved mortgage applications of CFPB banks, scaled by the total number of approved mortgages in the county in 2009, multiplied by 100.
Partitioning variables	
High $MktShare_{Non-CFPB}$	An indicator equal to one when the market share of a non-CFPB rival in the county in 2012 ($MktShare_{Non-CFPB}$) is above 10%, and zero otherwise.
High $Sold_{Non-CFPB}$	An indicator set to one when the fraction of approved loans that are sold ($Sold_{Non-CFPB}$) is above the sample median, and zero otherwise.
High Bad Yelp Review$_{CFPB}$	An indicator equal to one for a county with the proportion of CFPB banks that have at least one Yelp rating ≤ 3 out of 5 in the county from 2011 to the current year ($Bad\ Yelp\ Review_{CFPB}$) above the sample quintile, and zero otherwise.
High Google SVI	An indicator equal to one for counties in states with the state-level Google Search Volume Index (SVI) for the keyword "CFPB" ($Google\ SVI$) above the sample median, and zero otherwise.
High Education	An indicator equal to one for counties with the proportion of the population with a high school degree in 2012 ($Education$) above the sample median, and zero otherwise.
Bank-year variables	
ROE	Net income scaled by the book value of equity.
ROA	Net income scaled by total assets.
$PeerCPL_{CFPB}\_Agg(\%)$	The average of the county-level $PeerCPL_{CFPB}(\%)$ across all counties, weighted by the number of loan originations by a bank in each county.
Size	The natural logarithm of total assets.
Securities	Investment and traded securities scaled by total assets.
Deposit Rate	Interest expenses on deposits scaled by total deposits.

(continued)

Variable	Definition
Deposit	Total deposits scaled by total assets.
Real Estate Loans	Real estate loans scaled by total assets.
C&I Loans	Commercial and industrial loans scaled by total assets.
Unused Commitment	Unused loan commitments scaled by total assets.
Letters of Credit	Letters of credit scaled by total assets.

References

Agresti, A., 2021. Statistical Methods for the Social Sciences, fifth ed. Pearson.

American Financial Services Association, 2012. AFSA Comments on Disclosure of Consumer Complaint Data. July 19, 2012.

Angrist, J., Pischke, J., 2009. Mostly Harmless Econometrics: an Empiricist's Companion. Princeton University Press, Princeton, NJ.

Aobdia, D., Dou, Y., Kim, J., 2021. Public audit oversight and the originate-to-distribute model. J. Account. Econ. 72, 101420.

Badertscher, B., Shroff, N., White, H., 2013. Externalities of public firm presence: evidence from private firms' investment decisions. J. Financ. Econ. 109, 682–706.

Beatty, A., Liao, S., Yu, J., 2013. The spillover effect of fraudulent financial reporting on peer firms' investments. J. Account. Econ. 55, 183–205.

Begley, T., Purnanandam, A., 2021. Color and credit: Race, regulation, and the quality of financial services. J. Financ. Econ. 141, 48–65.

Bens, D., Berger, P., Monahan, S., 2011. Discretionary disclosure in financial reporting: an examination comparing internal firm data to externally reported segment data. Account. Rev. 86, 417–449.

Berenson, M., Levine, D., Szabat, K., Stephan, D., 2018. Basic Business Statistics: Concepts and Applications, fourteenth ed. Pearson.

Berger, P., Hann, R., 2007. Segment profitability and the proprietary and agency costs of disclosure. Account. Rev. 82, 869–906.

Bernard, D., 2016. Is the risk of product market predation a cost of disclosure? J. Account. Econ. 62, 305–325.

Biais, B., Gollier, C., 1997. Trade credit and credit rationing. Rev. Financ. Stud. 10, 903–937.

Cao, S., Du, K., Yang, B., Zhang, L., 2021. Copycat skills and disclosure costs: evidence from peer companies' digital footprints. J. Account. Res. 59, 1261–1302.

CFPB, 2013. Disclosure of Consumer Complaint Data. Docket No. CFPB-2012-0023. Final Policy Statement.

CFPB, 2015. Disclosure of Consumer Complaint Narrative Data. Docket No. CFPB-2014-0016. Final Policy Statement.

CFPB, 2016. Monthly Complaint Report. Consumer Financial Protection Bureau 10, April.

Chevalier, J., Mayzlin, D., 2006. The effect of word of mouth on sales: online book reviews. J. Market. Res. 43, 345–354.

Cohn, J., Liu, Z., Wardlaw, M., 2022. Count (and count-like) data in finance. J. Financ. Econ. 146, 529–551.

Consumer Mortgage Coalition, 2015. CMC Comments on Trade Secrets in Complaint Database. (Accessed 26 May 2015).

Cortés, K., Strahan, P., 2017. Tracing out capital flows: how financially integrated banks respond to natural disasters. J. Financ. Econ. 125, 182–199.

Darmouni, O., Sutherland, A., 2021. Learning about competitors: evidence from SME lending. Rev. Financ. Stud. 34, 2275–2317.

Dell'Ariccia, G., Friedman, E., Marquez, R., 1999. Adverse selection as a barrier to entry in the banking industry. Rand J. Econ. 30, 515–534.

Dell'Ariccia, G., Igan, D., Laeven, L., 2012. Credit booms and lending standards: evidence from the subprime mortgage market. J. Money Credit Bank. 44, 367–384.

Charoenwong, B., Kowaleski, Z., Kwan, A., Sutherland, A., 2023, RegTech. MIT Sloan Research Paper 6563–22. Available at: http://ssrncom/abstract=4000016.

Dou, Y., Roh, Y., 2023. Public disclosure and consumer financial protection. J. Financ. Quant. Anal. Forthcom. Available at: http://doi.org/10.1017/S0022109023000613.

Dou, Y., Ryan, R., Xie, B., 2018. The real effects of FAS 166/167 on banks' mortgage approval and sale decisions. J. Account. Res. 56, 843–882.

Durnev, A., Mangen, C., 2009. Corporate investments: learning from restatements. J. Account. Res. 47, 679–720.

Fudenberg, D., Tirole, J., 1986. A "signal-jamming" theory of predation. Rand J. Econ. 366–376.

Fuster, A., Plosser, M., Vickery, J., 2021. Does CFPB Oversight Crimp Credit? FRB of New York Staff Report No. 857. Available at: http://ssrn.com/abstract=3200020.

Gilje, E., Loutskina, E., Strahan, P., 2016. Exporting liquidity: branch banking and financial integration. J. Finance 71, 1159–1184.

Gormley, T., Matsa, D., 2014. Common errors: how to (and not to) control for unobserved heterogeneity. Rev. Financ. Stud. 27, 617–661.

Gurun, U., Matvos, G., Seru, A., 2016. Advertising expensive mortgages. J. Finance 71, 2371–2416.

Hastings, J., Madrian, B., Skimmyhorn, W., 2013. Financial literacy, financial education, and economic outcomes. Annual Review of Economics 5, 347–373.

Hayes, R., Jiang, F., Pan, Y., 2021. Voice of the customers: local trust culture and consumer complaints to the CFPB. J. Account. Res. 89, 1077–1121.

Huang, J., 2018. The customer knows best: the investment value of consumer opinions. J. Financ. Econ. 128, 164–182.

Imbens, G., Rubin, D., 2015. Causal Inference in Statistics, Social, and Biomedical Sciences. Cambridge University Press.

Jayaraman, S., Wu, J.S., 2019. Is silence golden? Real effects of mandatory disclosure. Rev. Financ. Stud. 32, 2225–2259.

Kang, J., Loumioti, M., Wittenberg-Moerman, R., 2021. The harmonization of lending standards within banks through mandated loan-level transparency. J. Account. Econ. 72, 101386.

Keys, B., Mukherjee, T., Seru, A., Vig, V., 2010. Did securitization lead to lax screening? Evidence from subprime loans. Q. J. Econ. 125, 307–362.

Kim, J., Valentine, K., 2021. The innovation consequences of mandatory patent disclosure. J. Account. Econ. 71, 101381.

Krieger, J., 2021. Trials and terminations: learning from competitors' R&D failures. Manag. Sci. 67, 5301–5967.

Leuz, C., Wysocki, P., 2016. The economics of disclosure and financial reporting regulation: evidence and suggestions for future research. J. Account. Res. 54, 525–622.

Li, V., 2016. Do false financial statements distort peer firms' decisions? Account. Rev. 91, 251–278.

Loutskina, E., Strahan, P., 2009. Securitization and the declining impact of bank finance on loan supply: evidence from mortgage originations. J. Finance 64, 861–889.

Loutskina, E., Strahan, P., 2011. Informed and uninformed investment in housing: the downside of diversification. Rev. Financ. Stud. 24, 1447–1480.

Luca, M., Zervas, G., 2016. Fake it till you make it: reputation, competition, and Yelp review fraud. Manag. Sci. 62, 3412–3427.

Manski, C., 1993. Identification of endogenous social effects: the reflection problem. Rev. Econ. Stud. 60, 531–542.

Marquez, R., 2002. Competition, adverse selection, and information dispersion in the banking industry. Rev. Financ. Stud. 15, 901–926.

Mian, A., Sufi, A., 2017. Fraudulent income overstatement on mortgage applications during the credit expansion of 2002 to 2005. Rev. Financ. Stud. 30, 1832–1864.

Milgrom, P., Roberts, J., 1982a. Limit pricing and entry under incomplete information: an equilibrium analysis. Econometrica 50, 443–459.

Milgrom, P., Roberts, J., 1982b. Predation, reputation, and entry deterrence. J. Econ. Theor. 27, 280–312.

Munnell, A., Tootell, G., Browne, L., McEneaney, J., 1996. Mortgage lending in Boston: interpreting HMDA data. Am. Econ. Rev. 86, 25–53.

Pence, K., 2006. Foreclosing on opportunity: state laws and mortgage credit. Rev. Econ. Stat. 88, 177–182.

Raval, D., 2020. Which communities complain to policymakers? Evidence from consumer sentinel. Econ. Inq. 58, 1628–1642.

Roychowdhury, S., Shroff, N., Verdi, R., 2019. The effects of financial reporting and disclosure on corporate investment: a review. J. Account. Econ. 68, 1–27.

Shroff, N., 2016. Discussion of "Is the risk of product market predation a cost of disclosure?". J. Account. Econ. 62, 326–332.

Smith, J., 1987. Trade credit and informational asymmetry. J. Finance 42, 863–872.

Sutherland, A., 2018. Does credit reporting lead to a decline in relationship lending? Evidence from information sharing technology. J. Account. Econ. 66, 123–141.

Tang, V., 2018. Wisdom of crowds: cross-sectional variation in the informativeness of third-party-generated product information on Twitter. J. Account. Res. 56, 989–1034.

Xie, B., 2016. Does fair value accounting exacerbate the procyclicality of bank lending? J. Account. Res. 54, 235–274.

Zou, Y., 2022. Strategic entry decisions, accounting signals, and risk management. Contemp. Account. Res. 39, 2338–2375.