Economic Consequences of Transparency Regulation: Evidence from Bank Mortgage Lending*

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Abstract

We examine the economic consequences of a rule designed to improve consumers' understanding of mortgage information. The 2015 TILA-RESPA Integrated Disclosures (TRID) rule simplifies the disclosures provided to consumers, reducing their information processing costs and increasing banks' secondary market frictions. We posit that TRID-affected mortgages become less attractive to banks as an investment opportunity. Our main results document that mortgage applications affected by TRID are less likely to be approved following the rule's effective date. We document evidence consistent with both a decrease in consumers' information costs and an increase in banks' secondary market frictions, providing insight into the potential channels through which this reduction in mortgage credit operates. We also find that banks partially compensate for reduced mortgage lending by increasing small business lending, and that fintechs absorb mortgage demand in areas with reduced mortgage lending by banks. Our study provides a better understanding of the broader economic consequences of transparency regulation for both the regulated firms and consumers, and provides a complementary perspective to the literature examining bank-level transparency in lending markets.

Keywords: Information processing costs, consumer disclosures, mortgage lending, banks, transparency regulation

JEL Classifications: D18, D83, G21, G28

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1 Introduction

We investigate the potential consequences of regulation designed to improve consumers' ability to process disclosures during the mortgage application process. Mortgage loans are financially complex transactions that most consumers engage in only a few times in their lives, typically at times when they are also moving homes. Prior research indicates that some households, particularly those with lower income and less education, obtain unfavorable mortgage terms due to the complexity of financial products offered to them (Campbell, 2006). Therefore, improving the ability of consumers to process information surrounding mortgage terms is an important policy objective of bank regulatory bodies, such as the Consumer Financial Protection Bureau (CFPB). The CFPB recently implemented a new rule, the TILA-RESPA Integrated Disclosures rule (hereafter, "TRID"), that simplifies the disclosures provided to consumers. Our study examines the broader consequences of this rule for banks. Thus, by considering disclosures to consumers in lending markets, we provide a novel and complementary perspective to the literature examining the consequences of bank-level transparency (Beatty and Liao, 2014; Bushman, 2014).

During the mortgage application process, consumers obtain information from required mortgage disclosures provided by lenders. Historically, these disclosures had disparate formats and were separately regulated by two federal statutes, the Truth-in-Lending Act (TILA) and the Real Estate Settlement Procedures Act (RESPA). The Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act) included a directive for the CFPB to implement an integrated and simplified disclosure. The motivation behind this directive was to protect consumers, to ensure a fair and efficient mortgage market, and to reduce disclosure complexity. Although the TRID rule did not change the information content of disclosures, it simplified the presentation of key information relevant to consumers, such as information about mortgage expenses. Importantly, TRID applies to only closed-end loans, defined as an extension of credit that is secured by a lien on a dwelling and is not an open-end line of credit. Open-end loans such as home equity lines of credit and reverse mortgages are exempt from the rule.

We posit two primary effects of TRID that reduce the relative attractiveness of mortgages from the lender's perspective. First, the simplified disclosures under TRID facilitate consumers' parsing of information in disclosures and comparisons of rates and fees across different lenders.[1] All else equal, consumers' improved understanding of mortgage information should reduce the interest and fees that banks are able to charge on mortgages. As we describe in Section 2.2, theory and empirical evidence in several settings is consistent with this potential outcome. Second, banks may face challenges in selling mortgages on the secondary market due to uncertainty about which party (i.e., the buyer or seller) is responsible for TRID violations. This uncertainty is ongoing, as banks note secondary market frictions in comment letters submitted several years after TRID (American Bankers Association et al., 2020). Furthermore, enhanced enforcement surrounding mortgage disclosures and a relatively large proportion of TRID violations have been consistently reported since the rule became effective. Taken together, these arguments suggest that following TRID, mortgages become less attractive to banks, relative to their other investment opportunities.[2] Combined with banks' funding and capital constraints, the reduction in relative attractiveness of mortgages should result in banks reducing their TRID-affected mortgage lending and reallocating those funds to other investment opportunities.

Our sample is comprised of mortgage applications reported under the Home Mortgage Disclosure Act (HMDA) from 2011 to 2019. We conduct our tests at the application-level, which allows us to account for a rich set of applicant characteristics, loan characteristics, and time-varying county-specific economic conditions that affect the probability of approval. We use a control group to help address the inherent challenge of separating the effects of TRID from other changes in the mortgage lending market following the 2007-2009 financial crisis. Although TRID applies to all lenders with non-trivial mortgage issuance, it only applies to closed-end mortgages. Therefore, we use a difference-in-differences (DiD) design which designates closed-end loan applications as the treatment group and open-end loan applications as the control group. Exploiting within-bank-year variation in whether or not the application is affected by TRID mitigates concerns that we are simply capturing bank-level changes in mortgage lending following TRID.

[1] TRID applies to all lenders that issue more than five mortgages in a year. However, our tests focus on banks in order to ensure that the lenders we examine face similar regulatory requirements and financing constraints. Hereafter, we use "bank" and "lender" interchangeably, except where noted in additional tests of fintech lending and aggregate lending from all lenders (banks and nonbanks).

[2] We note that our prediction does not require both effects to be present for each application. For example, even if some borrowers are willing to incur their pre-TRID interest rate and fees, secondary market frictions should still reduce the relative attractiveness of their loans from the bank's perspective. Similarly, even if the risk of TRID violations is low for some loans, the interest rate and fees that can be charged for those loans may still be reduced.

Our DiD design assumes that the change in approval probability of open-end mortgage applications provides a reasonable counterfactual for the equivalent change for closed-end mortgage applications had they not been affected by TRID. To ensure similarity in observable applicant characteristics between the treatment and control groups, we estimate entropy-balance-weighted regressions. We also examine whether the two groups exhibit differential pre-TRID trends in approval probability to support the plausibility of the parallel trends assumption.

Our main finding is a decrease in the probability of approval of TRID-affected mortgage applications at banks post-TRID. Our inference is that banks change their lending decisions following the rule's effective date. We then provide evidence to corroborate our argument that, for the bank, TRID reduces the relative attractiveness of investing in closed-end mortgages. Specifically, we find evidence consistent with a decrease in borrowers' information processing costs and an increase in banks' secondary market frictions after TRID.

We next examine whether banks appear to redirect funds to other lending opportunities, namely small business lending. Under the Community Reinvestment Act (CRA), regulators evaluate the collective amount of mortgage lending and small business lending to low- and moderate-income individuals. Therefore, small business lending may provide an alternative investment opportunity that allows banks to offset the relative decrease in mortgage lending in certain areas while still complying with the CRA. Using information reported by banks under the CRA, we document increased small business lending in counties in which banks reduce their closed-end mortgage approval rates following TRID. This result suggests that banks redirect some of their funds from closed-end mortgage lending to small business lending in the same county.

While our main tests focus on traditional banks, the use of technology by non-depository institutions means they could respond differently to the effects of TRID. We explore whether fintechs absorb some of the demand for closed-end mortgages that is unmet by banks. We follow prior literature and define a fintech as a lender that has a complete end-to-end online mortgage application and approval process (Fuster et al., 2019). Fuster et al. (2019) finds that, compared to other lenders, fintechs process mortgage applications more quickly and adjust their supply of credit more elastically. Moreover, even though fintechs (and nonbank lenders) are also subject to TRID, they may be subject to relatively less oversight compared to commercial banks. Specifically, multiple supervisory authorities are involved in examining banks, while the CFPB is the primary regulator for fintechs. Although the Dodd-Frank Act allows the CFPB to examine fintechs, this provision was largely unused during our sample period.[3] For these reasons, fintechs may be able to increase their market share in certain areas following TRID. Using HMDA data for a sample of fintech lenders identified in Buchak et al. (2018) and Fuster et al. (2019), we document that fintechs approve more mortgage credit in counties in which banks reduce closed-end mortgage approval rates to a greater extent. The findings of this test suggest that fintechs shift their lending to at least partially absorb some of the unmet demand for closed-end mortgages.

We also investigate changes in the aggregate lending market following TRID. It is possible that consumers' improved understanding of mortgage terms motivates them to submit more complete applications, thereby increasing demand for closed-end mortgages. We do not find support for this explanation when aggregating applications to all commercial banks to the county-year level and examining both total applications submitted and total approved credit. However, we find evidence of increased demand when examining applications to all lenders. Specifically, we find an increase in total applications submitted and aggregate closed-end credit approved following TRID. These results are consistent with an increase in closed-end mortgage demand following TRID and with this increased demand being largely met at non-depository institutions. These tests have the additional benefit of addressing an alternative explanation for our reduced approval probability results—that an increase in submitted applications to banks fully explains the decrease in approval probability.

We investigate an additional alternative explanation related to consumer application choices. The increased comparison shopping related to TRID is measured as an increase in incomplete or withdrawn applications. If these consumers would have been approved had they completed the application process, this selection issue could mechanically reduce the approval probability. Additional analyses to assess the sensitivity of our results to varying levels of this selection concern suggest it would need to be quite large in order to fully explain our results.

We also address alternative explanations related to banks' incentives to change lending decisions. Given our research design, an alternative explanation would need to affect closed-end and open-end loans differentially *within* a bank-year and be contemporaneous to TRID. Potential confounding events include other contemporaneous regulation required by the Dodd-Frank Act, including the

[3] See discussion at https://www.consumerfinance.gov/about-us/newsroom/cfpb-invokes-dormant-authority-to-examine-nonbank-companies-posing-risks-to-consumers/.

2014 amendments to Regulation Z and the 2015 retained risk requirements surrounding asset-backed securitization transactions. The evidence across these additional tests supports our inference that banks' response to other regulations is unlikely to fully explain our results.

Our study contributes to several literatures. First, we contribute to the literature on information processing costs. Multiple prior papers find that reducing investors' information processing costs benefits capital market participants (Blankespoor, deHaan, and Marinovic, 2020). For example, investors and firms enjoy greater liquidity when investors' processing costs decrease (e.g., Lang and Stice-Lawrence, 2015; Blankespoor, deHaan, and Zhu, 2018). Studies examining disclosure transparency in consumer markets also find benefits associated with improving consumers' processing of information (e.g., Stango and Zinman, 2016).[4] However, reducing disclosure processing costs also imposes constraints on the regulated firms. For example, deHaan, Song, Xie, and Zhu (2021) finds that high-fee mutual funds exit the market following regulation introducing simplified summary disclosures for investors. We contribute to this literature by showing that transparency regulation designed to benefit consumers may induce firms to take actions to offset their costs associated with this regulation.

Second, we contribute to the literature on lending market transparency. Transparency in lending markets is important, as banks have substantial private information about their borrowers and may need to be opaque to engage in maturity transformation (Dang, Gorton, Holmström, and Ordonez, 2017). Prior studies examine the consequences of bank-level transparency for bank outcomes, such as bank risk (Bushman and Williams, 2015), regulatory forbearance (Gallemore, 2022), and bank stability (Granja, 2018). We provide a complementary view to this literature by focusing on the consequences of transparency regulation targeting information provided to borrowers. Prior studies focus on the consequences for consumers of more transparent disclosure (Wang and Burke, 2021; Kielty, Wang, and Weng, 2021). By documenting the consequences for banks, we provide novel insight into the effects of lending market transparency.

Finally, our results should inform regulators about the potential consequences of TRID for the mortgage market. This market is economically large, representing $15.4 trillion in outstanding debt as of 2018, and mortgages comprise one of the largest loan categories on most banks' balance sheets.

[4] One exception is Christensen et al. (2020), which finds that price transparency regulation in the healthcare industry may not be effective due to firms' flexibility in implementing the regulation.

The CFPB "is committed to mortgage disclosures that provide consumers with the information they need to make better-informed mortgage decisions without imposing unnecessary or undue regulatory burdens on firms" (CFPB, 2020b). However, recent comment letters from banks suggest that the implementation of TRID has been costly. For example, one comment letter states: "The TRID rule has changed how creditors process mortgage loan applications and concerns have surfaced that credit availability may have been reduced to some extent by TRID because creditors seek to avoid TRID violations" (Cooperative Credit Union Association, 2020). Our results suggest that banks' concerns that they would have to reduce credit availability may have merit. These findings should be of particular interest to the CFPB given its stated objectives of ensuring access to credit and prohibiting discrimination in credit transactions (e.g., CFPB, 2020a).

We note important caveats to our study. First, our focus is lenders' response to TRID and we are unable to draw conclusions regarding the overall net benefits or costs of the rule (e.g., trading off the costs and benefits of reduced bank mortgage lending vs. increased small business lending, lower interest rates vs. lower credit availability). Second, our data cover the time period spanning a few years after the passage of the rule, and we therefore cannot draw conclusions regarding longer-term consequences. Third, the TRID rule was passed following the 2007-2009 financial crisis and became effective in a time period when many changes occurred in the banking industry. Although we take multiple steps to address alternative explanations, our results are primarily descriptive in nature and should be interpreted accordingly.

2 Institutional Background and Predictions

2.1 Overview of TRID

The TRID rule, also known as the "Know Before You Owe" rule, became effective on October 3, 2015. The purpose of this disclosure rule reflects the motivation for mortgage regulation more broadly: (1) to improve borrowers' ability to understand information, (2) to protect consumers who may have limited financial literacy and may later regret the terms of their mortgage, and (3) to lower the incidence of foreclosures, which can contribute to macroeconomic instability (Campbell et al., 2011). TRID applies to all creditors who make at least five mortgages per year. The rule applies only to closed-end mortgages, defined as an extension of credit for a fixed amount secured by a lien on a dwelling and that is not an open-end line of credit. Open-end loans such as home equity lines of credit and reverse mortgages are exempt from the rule.

One of TRID's primary changes was to simplify the disclosures provided to mortgage applicants. Although TRID does not change the information content of the disclosures, it streamlines the number and timing of forms provided, as well as the presentation of information within the forms. Specifically, TRID requires lenders to provide a single disclosure within three days after receiving the loan application (Loan Estimate) and a single disclosure at least three days before closing (Closing Disclosure). Figure 1 presents a timeline of a hypothetical mortgage loan application and origination process, including the timing of the two disclosures.

The Loan Estimate and Closing Disclosure each replace multiple disclosures. Prior to TRID, borrowers received up to four different disclosures under two separate federal statutes: (1) the Truth-in-Lending Act (TILA), regulated by the Federal Reserve Board (FRB), and (2) the Real Estate Settlement Procedures Act (RESPA), regulated by the Department of Housing and Urban Development (HUD). After submitting an application, borrowers received the Good Faith Estimate, provided by the lender or mortgage broker and regulated by RESPA, and the Truth in Lending (TIL) disclosure, provided by the lender and regulated by TILA. After TRID became effective, borrowers receive a single Loan Estimate after submitting the application. Similarly, prior to TRID, borrowers received the finalized mortgage terms via two disclosures: the HUD-1 Settlement statement, provided by the settlement agent and regulated by HUD, and the final TIL disclosure, provided by the bank and regulated by TILA. After TRID became effective, borrowers receive a single Closing Disclosure prior to closing. Figure 2 presents an illustrative example of the TRID-imposed streamlining between the old disclosures (top row) and the new disclosures (bottom row, red dashed lines).

In addition to reducing the number of disclosures, TRID also requires a new simplified format that reduces inconsistencies and duplication of information. Kielty et al. (2021) finds a 14% reduction in line items and a 65% reduction in words in the new Loan Estimate, compared to the old disclosures it replaced. Under the old rules, due to the separate federal agencies that regulated the disclosures, the presentation of information between the two initial disclosures and the two subsequent disclosures was inconsistent. Panels A and B of Figure 3 present the format of the initial Good Faith Estimate and the final HUD-1 Settlement Statement, respectively, both regulated by HUD under RESPA. The format is inconsistent across the two disclosures. Panel C presents the format of the initial and final TIL disclosures, regulated by TILA. The format is the same between the initial and final disclosures, but it is inconsistent with the formats of the two HUD disclosures in Panels A and B. Figure 3, Panel D presents the format of the new TRID disclosures, which reflects the new consistency between the Loan Estimate and Closing Disclosure.

TRID also changes other requirements surrounding disclosures. First, TRID reallocates responsibility for disclosures from settlement agents to creditors. Second, TRID changes thresholds regarding the extent to which a certain fee can change from the Loan Estimate to the Closing Disclosure without providing the consumer with a revised disclosure. The zero tolerance prohibition on cost increases in some categories of charges results in the need to provide a revised disclosure if there are any fee changes in those categories.

2.2 Borrower Information Costs

The provision of a single disclosure in a simplified format under TRID should reduce borrowers' information processing costs for two related reasons. First, the simplified format and integrated nature of the new disclosures should improve borrowers' ability to compare interest rates and fees across multiple banks' Loan Estimates. For example, the Quantitative Study conducted by the CFPB to test consumers' ability to identify key information in the pre-TRID vs. post-TRID disclosures finds that 79.5% of respondents could correctly identify the APR when presented with the post-TRID disclosures, an increase from 65.7% for the pre-TRID disclosures (CFPB, 2020b).

Second, the consistent presentation of information between the Loan Estimate and Closing Disclosure helps applicants ascertain changes in interest rates and fees between the Loan Estimate and Closing Disclosure for a given lender. Thus, TRID could prevent lenders from engaging in "bait-and-switch" tactics, whereby they might entice a borrower with low fees in an initial set of disclosures, then present changes to the terms of the agreement in the final set of disclosures before closing. Complex disclosures and inconsistent presentation of information between the initial and final disclosures plausibly facilitate increases in fees that may go unnoticed by the borrower. Furthermore, borrowers often were given little time to read the disclosures to understand how the terms may have changed. TRID requires lenders to provide the Closing Disclosure at least three days before mortgage closing.

If borrowers can easily compare interest rates and fees across disclosures, banks should be less able to charge high interest rates and fees (Gabaix and Laibson, 2006; Carlin, 2009).[5] Prior research documents that borrowers with the same characteristics pay significantly different mortgage rates on identical loans, and borrowers' financial knowledge is a key determinant of rates (Bhutta et al., 2020). In addition to facilitating high interest rates, complexity can also facilitate high fees. One category of fees is origination charges, which can include points, application fees, and underwriting fees.[6] The Loan Estimate provides detailed information regarding specific fees, including the application fee, underwriting fee, appraisal fee, and credit report fee. As a result of consumers' improved understanding of mortgage terms, TRID should reduce the fees and interest that banks charge. Consistent with this intuition, Kielty et al. (2021) find that first-time home buyers are charged lower interest rates relative to repeat home buyers following TRID.

2.3 Secondary Market Frictions

A specific type of friction that banks may face is difficulty in selling mortgages on the secondary market. There are two possible reasons why TRID may result in secondary market frictions. First, there was uncertainty and ambiguity regarding which party (the buyer or seller) would be responsible for TRID violations. The uncertainty appears to be ongoing as comment letters from 2020 continue to highlight this issue. For example, when discussing the ambiguity surrounding which party (i.e., the buyer or seller) is responsible for TRID violations when the loan is sold, the American Bankers Association and other related agencies state: "This lack of certainty has unnecessarily hindered the sale of loans, resulting in reduced credit availability" (American Bankers Association et al., 2020). Second, there is enhanced enforcement surrounding mortgage disclosures and a relatively large proportion of TRID violations have been consistently reported since the rule was effective. The increased oversight and enforcement reduces the benefit associated with secondary market sales. For example, if lenders are responsible for handling TRID violations of

[5] For example, product complexity and consumers' lack of knowledge are associated with high fees paid by consumers in several consumer financial product markets, such as retail structured products (Célérier and Vallée, 2017), mutual funds (Hortaçsu and Syverson, 2004; Barber et al., 2005; Choi et al., 2010; Anagol and Kim, 2012; deHaan et al., 2021), credit cards (Stango and Zinman, 2016), social security (Duarte and Hastings, 2012), and life insurance (Brown and Goolsbee, 2002).

[6] Prior literature finds that discount points generally increase borrowers' monetary losses (Agarwal et al., 2017). Points are charged to the borrower upfront and are calculated as a percentage of the loan amount. Some lenders use points to offer a lower interest rate. Origination charges are due to the bank, regardless of whether the bank retains the mortgage loan on its balance sheet or sells it on the secondary market.

sold loans, they will prefer to sell relatively fewer closed-end loans due to the possibility of needing to bring them back onto the balance sheet. Similarly, if mortgage buyers are responsible, they will prefer to purchase relatively fewer closed-end loans due to the fact that mortgages with TRID violations cannot be included in mortgage-backed securities. Collectively, the reduced ability to sell loans on the secondary market can reduce credit supply, because banks cannot easily increase the amount of loans held on-balance sheet due to regulatory capital requirements (Beatty and Liao, 2014). These secondary market frictions should reduce the relative attractiveness of TRID-affected mortgages.

2.4 Primary Prediction

Sections 2.2 and 2.3 outline two potential effects of TRID that may reduce the relative attractiveness of closed-end mortgages to banks and affect their lending decisions. Specifically, TRID-affected mortgages should be associated with lower interest and fees as well as greater secondary market frictions. Collectively, these two effects likely make closed-end mortgages less attractive to lenders, compared to investment opportunities unaffected by TRID. Given that external financing frictions prevent banks from approving all loan applications made by credit-worthy borrowers, banks will reduce their mortgage issuance due to the inability to hold all of the mortgages on their balance sheet. Therefore, our primary prediction is that the likelihood of application approval for mortgages affected by TRID decreases following the rule's effective date.

Importantly, our prediction does not require both effects to be present for all applications. For example, although we predict a reduction in interest rates and fees on average, some consumers may still be willing to incur their pre-TRID interest rate and fees in order to obtain a mortgage loan. For these consumers, banks are still subject to secondary market frictions, which should also reduce the relative attractiveness of these loans from the bank's perspective. Similarly, although we predict a reduction in the likelihood of loan sales on average, some banks may not have intended to sell some consumers' loans on the secondary market. For these loans, banks are still affected by consumers' improved understanding of mortgage interest rates and fees, which should also reduce the relative attractiveness of making these loans.

3 Sample Selection and Research Design

3.1 Sample Selection

Our primary data source is mortgage application information required by the Home Mortgage Disclosure Act (HMDA). For each application they receive, financial institutions affected by HMDA disclose the ultimate outcome (e.g., approved and originated, approved and not originated, denied, withdrawn, or incomplete), application year, applicant characteristics (e.g., income level, race), loan characteristics (e.g., loan type, loan amount, lien status), and property characteristics (e.g., county location). Although the database provides a rich set of information, certain information is not included. Specifically, identifying information regarding the property address, specific applicant identifiers, and whether the loan defaults are not included in the dataset. Although we can identify the year in which each application was submitted, we do not have data on the month or day of the application.

Our sample construction begins with all home purchase and refinancing applications for one-to-four family housing in the HMDA database between 2011 and 2019. We exclude applications in 2015, the year in which the TRID disclosures were implemented, because the month and day of the application (which are unavailable in HMDA) are necessary to determine if a 2015 application is received before or after TRID's effective date of October 3, 2015. This sample period allows for a pre-period of 2011 - 2014 and a post-period of 2016 - 2019. Consistent with Dou et al. (2018), we impose the following sample screens on the remaining applications: (1) approved or denied loans only, (2) applicant income is greater than \$10,000, and (3) loan amount is greater than \$1,000.[7]

On the lender side, we focus on commercial banks filing the Report of Condition and Income (Call Report). Restricting our sample to banks and excluding non-depository lending institutions (i.e., "shadow" banks) results in a more homogeneous sample of lenders that face similar regulatory requirements and financing constraints.[8] We use the Reporter Panel in the HMDA database to link the HMDA bank identifier to the bank identifier in the Call Reports. To ensure that our sample

[7] Sample screen (1) applies to our main test. The possible HMDA action groups included in any of our tests are: approved and originated, approved and not originated, denied, withdrawn, and incomplete. Approved loans include both approved and originated and approved and not originated loans. Appendix B provides a summary of the HMDA action group samples used in each test.

[8] We explore fintech mortgage lending in tests presented in Section 5.4. Berg et al. (2022) provide a review of fintech lending and Buchak, Matvos, Piskorski, and Seru (2018) provide more information about the share of shadow banks in the mortgage market.

banks are active in the mortgage market, we require each bank to receive an average of at least 200 applications per year and to hold an average of at least 25% of its loan portfolio in mortgages across all years (Xie, 2016). To avoid contaminating our sample with banks' acquisition and divestiture activity, we remove applications made in years when the bank had an annual change in total assets of more than 25%. We further restrict our sample to only include applications made to banks with both open-end and closed-end mortgage applications in both the pre-period and post-period.

We use closed-end loan applications as our treatment sample and open-end loan applications as the control sample. The HMDA dataset does not provide information on whether an application is for a closed-end or open-end loan until 2018. We use a machine learning approach (Classification and Regression Trees, or CART), trained on applications post-2018, to classify applications throughout our sample period as closed-end or open-end using observable loan characteristics. We provide a detailed discussion of the technique and performance of this classification approach in Appendix C. Our final sample includes 19,455,329 closed-end and open-end applications for 7,359 unique bank-years.

3.2 Research Design

We examine whether the likelihood of application approval changes following TRID for closed-end applications relative to open-end applications. The unit of analysis is a mortgage application. We estimate the following entropy-balance-weighted linear probability model on the sample of all approved or denied loans in our sample:

$$\begin{aligned} Approval_{i,j,t} = {} & \beta_1 Post_t \times Closed_{i,j,t} + \beta_2 Closed_{i,j,t} + \delta Applicant\_Characteristics_{i,j,t} \\ & + \theta Loan\_Controls_{i,j,t} + \gamma Bank\_Controls_{i,t-1} \\ & + \Sigma \alpha_i Bank_i + \Sigma \alpha_{k,t} County\text{-}Year_{k,t} + \epsilon_{i,j,t}, \end{aligned} \tag{1}$$

where $Approval_{i,j,t}$ is an indicator variable set equal to one if bank i approves borrower j's application in year t and zero if the bank denies the application. *Post* is an indicator variable set equal to one for applications submitted from 2016 to 2019 and zero for applications submitted from 2011 to 2014. *Closed* is our treatment indicator and is equal to one if the application is for a closed-end loan and zero if the application is for an open-end loan. We predict a negative β_1 if applications affected by the rule are associated with a relative decrease in approval probability in the post-TRID period.

We include a vector of $Applicant\_Characteristics_{i,j,t}$ to account for the applicant's demographic characteristics and financial position: indicator variables capturing whether the applicant is female ($Female$), Black ($Black$), or Hispanic ($Hispanic$), and the log of applicant income ($ApplicIncome$). Equation (1) also includes $Loan\_Controls_{i,j,t}$, which is a vector of four loan-level variables including: the log of the loan amount ($LoanAmount$), indicator variables capturing whether the mortgage is conventional ($Conventional$), for an owner-occupied principal dwelling ($OwnerOccupied$), and for a refinancing ($Refinance$) as opposed to a home purchase.[9]

We also control for a vector of time-varying bank characteristics, $Bank\_Controls_{i,t-1}$, that may influence the ability of a bank to issue loans. We control for the log of total assets ($BankSize$) and several proxies for financial performance, the ratio of Tier 1 capital to risk-weighted assets ($Tier1$), the ratio of net income to total assets (ROA), and the ratio of non-performing loans to total loans (NPL). To capture variation in bank business models, we control for the ratio of noninterest income to total assets ($NonInterestIncome$) and the ratio of total investment securities to total assets ($Securities$). We include the ratio of deposit interest expense to total deposits ($DepositIntRate$) to capture the cost of deposits. Finally, to control for funding sources, we include growth in core deposits ($CoreDepositGrowth$) and growth in wholesale funding ($WSFgrowth$). Detailed variable definitions of all application-level and bank-year-level characteristics are provided in Appendix A.

The model further includes property county-year fixed effects to account for local economic conditions affecting all applications within a county-year.[10] We also include bank fixed effects to account for time-invariant unobservable characteristics specific to each sample bank. In a second specification, we include bank-year fixed effects in addition to property county-year fixed effects. This specification allows us to account for unobservable characteristics that apply to all applications within a bank-year.[11] Due to the large number of fixed effects, we use a linear probability model rather than a nonlinear model, as prior literature shows that fixed effects in nonlinear models can yield biased and inconsistent coefficients (Greene, 2004). Standard errors are clustered by bank

[9] We exclude the log of the ratio of the loan amount to applicant income as a control variable, because we include both the loan amount and applicant income as control variables.

[10] *Post* is subsumed by these fixed effects.

[11] Bank-year-level control variables are subsumed in this specification.

and county-year, which allows for correlation in error terms for all applications within a given bank and correlation all applications within a given county-year.

4 Main Results

4.1 Descriptive Statistics

For most of our tests, our sample includes 19,455,329 approved and denied applications. We provide a summary of the sample and unit of analysis for each test in Appendix B. We present descriptive statistics for application-level and bank-year-level characteristics in Table 1. The table shows that approximately 79.6% of loans in the main sample are approved. Of the 22,250,066 approved, denied, incomplete, and withdrawn applications, 12.6% are incomplete or withdrawn ($NoDecision$). The sample is skewed towards treatment observations as *Closed* applications comprise 95.4% of the sample. On average, applicant income is $121,627, and 28.7% (7.9%) [14.0%] of applications are submitted by female (Hispanic) [Black] applicants. The average loan size is approximately $235,780. The majority of applications involve conventional loans (89.1%) and owner-occupied principal dwellings (87.5%). More than half of the sample (62.2%) is refinancing applications.

The average bank size is approximately $11.1 billion in total assets across all 7,359 bank-years in our sample. The Tier 1 capital ratio is 15.3%, well above the minimum to be considered well-capitalized under regulatory requirements. On average, investment securities comprise approximately 19.5% of banks' asset bases, and non-interest income is 1.1% of total assets. The average ROA is 1.1%, the average interest expense on deposits is 0.6%, and non-performing loans are 1.6% of the loan portfolio. Annual core deposit growth and wholesale funding growth are approximately 4.3% and 9.8%, respectively.

Our research design relies on the use of open-end mortgages as a control group for closed-end mortgages. To mitigate concerns regarding observable differences between the two groups, we employ entropy balancing. This approach uses a reweighting scheme on the control group observations that allows us to obtain covariate balance across three moments (mean, variance, and skewness) and can reduce model dependence in estimating treatment effects (Hainmueller, 2012). We entropy balance on the four applicant characteristics to ensure that the treatment and control observations have similar applicant pools. However, given that open-end and closed-end loans have different features, by definition, we do not balance the samples on loan characteristics. For example, given the open-end status allowing for a line of credit, its loan amount is smaller than a similar closed-end loan for a fixed amount.

Panel B of Table 1 presents descriptive statistics for the applicant characteristics of closed-end and open-end applications separately. For each applicant characteristic, we present the mean, variance, and skewness within: (1) closed-end applications, (2) pre-balancing open-end applications, and (3) post-balancing open-end applications (i.e., after applying the weights from entropy balancing). The panel shows that the closed-end and open-end samples obtain a high degree of covariate balance across three moments after employing entropy balancing. Panel C of Table 1 presents descriptive statistics of the loan characteristics separately for closed-end and open-end applications. As expected, given the different features of closed-end and open-end loans, closed-end loans involve larger amounts and have fewer conventional, owner-occupied, or refinancing applications.

4.2 Likelihood of Mortgage Approval

Our main prediction is that applications affected by TRID are associated with reduced mortgage application approval rates. We test this prediction by examining whether the change in the likelihood of approval for the treatment group of closed-end loans is different from the equivalent change for open-end loans. Table 2 reports the results of estimating equation (1), described in Section 3.2. Both columns include applicant characteristics, loan controls, and county-year fixed effects. Column (1) accounts for bank characteristics using bank fixed effects and time-varying bank-year-level control variables, while column (2) uses bank-year fixed effects. We find a negative and significant coefficient on the interaction term $Post \times Closed$ in both columns. The economic magnitude of the estimate in column (2) is a 5.1 percentage point decrease in the likelihood of approval, which corresponds to approximately 6.4% of the unconditional likelihood of approval of 79.6% (5.1%/79.6%=6.4%). These results indicate that closed-end applications are associated with a reduced likelihood of application approval following the effective date of TRID. Our inference is that banks restrict mortgage credit supply for applications affected by TRID in response to the rule.

The identifying assumption of our DiD regression is that the approval probabilities of the treatment and control groups would have trended similarly absent treatment (parallel trends assumption). To support the plausbility of this assumption, we plot the $Year \times Closed$ coefficients from estimating a version of Equation (1) that replaces $Post$ with indicators for each year of application submission. Figure 4 plots these coefficients estimates, relative to the last pre-TRID period, 2014. The shaded areas around the coefficients reflect the 95% confidence intervals. The approval probabilities for the two groups do not appear to be trending differently pre-TRID. In contrast, the post-TRID coefficients reveal a decrease in the likelihood of approval for closed-end loans relative to open-end loans.

5 Mechanisms and Lender Actions

We posit that the reduction in mortgage approval probability is a consequence of the reduced relative attractiveness of TRID-affected mortgages from the bank's perspective. This lower attractiveness following the rule's effective date occurs for a combination of two reasons: (1) a reduction in borrower information costs and (2) an increase in secondary market frictions faced by lenders. We provide analyses in the following sections to corroborate these mechanisms and provide insight into lender actions to partially compensate for reduced mortgage lending.

5.1 Borrower Information Costs Mechanism

This section presents results of two tests investigating whether the simplified disclosures reduce the borrowers' costs of processing information about mortgage costs. The first test examines the prevalence of comparison shopping, which should increase if the borrower's costs of processing information decrease. The second test examines interest rates offered by lenders, which should decrease if lenders are disciplined by consumers' better understanding of mortgage information.

5.1.1 Comparison Shopping

We first test whether applications affected by TRID are associated with a relative increase in consumers' comparison shopping. Consumers' lower information processing costs should increase the expected net benefits of comparison shopping (i.e., obtaining Loan Estimates from more than one lender), resulting in an increase in the number of submitted applications. The HMDA dataset also provides information to determine whether each application did not receive a final decision of approved or denied, because the application was withdrawn or left incomplete. Given that TRID only requires six pieces of information to be submitted in order to receive the Loan Estimate, it is likely that applicants received initial potential loan terms in these cases and could be using the information for comparison shopping purposes.[12] To study comparison shopping, we expand the application-level sample in our main tests to include all approved, denied, withdrawn, and incomplete loan applications and estimate the following equation on this expanded sample of 22,250,066 applications:

$$\begin{aligned} NoDecision_{i,j,t} = {} & \beta_1 Post_t \times Closed_{i,j,t} + \beta_2 Closed_{i,j,t} + \delta Applicant\_Characteristics_{i,j,t} \\ & + \theta Loan\_Controls_{i,j,t} + \gamma\beta_{i,t} Bank\_Controls_{i,t-1} \\ & + \Sigma\alpha_i Bank_i + \Sigma\alpha_{k,t} County\text{-}Year_{k,t} + \epsilon_{i,j,t}. \end{aligned} \tag{2}$$

The dependent variable is $NoDecision$, an indicator equal to one if the application is withdrawn or left incomplete (i.e., the bank does not make a final approval/denial decision), and zero otherwise (i.e., the application is approved or denied). Panel A of Table 1 shows that 12.6% of approved, denied, withdrawn, and incomplete applications are withdrawn or left incomplete. All other variables are discussed in Section 3.2. If comparison shopping increases to a greater extent for treatment group applications than for control group applications, we expect a positive coefficient on the interaction term $Post \times Closed$.

We present results of estimating equation (2) in Table 3, Panel A. Both columns include county-year fixed effects. In addition, column (1) includes bank fixed effects and bank-year-level controls while column (2) includes bank-year fixed effects. Across both columns, we find a positive and significant coefficient on $Post \times Closed$. This finding indicates that closed-end loan applications are more likely to be withdrawn or left incomplete by the applicant following the effective date of

[12] Specifically, the requirement to provide a Loan Estimate is triggered when an applicant submits the following information to the bank: (1) consumer's name; (2) consumer's income; (3) consumer's social security number to obtain a credit report; (4) property address; (5) an estimate of the value of the property; and (6) mortgage loan amount sought. See https://www.consumerfinance.gov/compliance/compliance-resources/mortgage-resources/tila-respa-integrated-disclosures/tila-respa-integrated-disclosure-faqs/#providing-loan-estimates for more information.

TRID, relative to open-end loan applications. Given that consumers should have received Loan Estimates for all of the applications in this sample, the results suggest that the simplified disclosures facilitate comparison shopping.

5.1.2 Offered Interest Rates

Borrowers' better understanding of mortgage information should reduce the interest rates and fees banks are able to charge. Thus, we expect that interest rates on TRID-affected mortgages decrease to a greater extent relative to unaffected mortgages following TRID. Our analysis uses data on interest rates from RateWatch (now S&P Global), a third-party data provider that surveys bank branches to obtain interest rates offered on various products.[13] We use rates offered on $175,000 30-year fixed rate mortgages to capture closed-end mortgage interest rates. We proxy for rates on open-end loans using rates for home equity lines of credit (HELOCs) up to 80% of loan-to-value (LTV).[14]

We aggregate the branch-level information in the RateWatch dataset to the bank-county-year level using the FDIC's Summary of Deposits (SOD) dataset, which includes information on every bank branch in the United States. Specifically, we take the average interest rate offered by all of a bank's branches operating in a specific county-year. Our final sample includes up to two rates (i.e., one closed-end and/or one open-end) per bank-county-year: the average rate offered on closed-end loans (30-year fixed mortgages) and the average rate offered on open-end loans (HELOCs). Because RateWatch changed the surveyed loan amounts for HELOCs beginning in 2018, we use a sample period of 2013 - 2014 as the pre-period and 2016 - 2017 as the post-period to maintain balanced pre-TRID and post-TRID sample periods. Using this sample, we estimate the following regression:

$$\begin{aligned} InterestRate_{c,i,k,t} =& \beta_1 Post_t \times ClosedRW_{c,i,k,t} + \beta_2 ClosedRW_{c,i,k,t} + \Sigma\alpha_i Bank_i \\ &+ \Sigma\alpha_{k,t} County\text{-}Year_{k,t} + \epsilon_{c,i,k,t}, \end{aligned} \tag{3}$$

[13] We conduct this analysis using RateWatch data at the bank-county-year level rather than HMDA data at the individual application level, because interest rate information in the HMDA dataset is sparsely populated before 2018. Specifically, before 2018, the loan rate spread, defined as the difference between the APR and the interest rate of the Treasury security of comparable security, is only required to be reported in HMDA if the spread exceeds the threshold set by the Board in Regulation C.

[14] Each branch's HELOC rates can be surveyed for varying loan amounts (e.g., $50,000, $100,000). When a branch is surveyed for multiple loan amounts, our tests use the most frequently surveyed amount that is available in both the pre- and post-period for each bank-county.

where c indexes the closed-end status of the rate, i indexes the bank, k indexes the county location of the branch, and t indexes the year. $ClosedRW$ is an indicator variable equal to one if the surveyed RateWatch rate is for a closed-end loan and zero if the surveyed rate is for an open-end loan.[15] Equation (3) effectively compares the change in rates from the pre- to post-period for closed-end loans to the equivalent change for open-end loans. If banks reduce offered interest rates for closed-end mortgages, we expect to find a negative coefficient on the interaction term.

Table 3, Panel B presents the results of estimating equation (3). Column (1) finds a negative coefficient on the interaction term $Post \times ClosedRW$. This result suggests that following the effective date of TRID, offered rates decrease for closed-end mortgages compared to the control group of open-end loans. Column (2) replaces the bank fixed effects with bank-year fixed effects. We continue to find a negative and significant coefficient on the interaction term. Collectively, the results in Table 3 provide evidence consistent with our argument that TRID reduces borrowers' information processing costs, thereby facilitating comparison shopping and constraining high interest rates and fees. From the bank's perspective, this outcome reduces the relative attractiveness of closed-end mortgages.

5.2 Secondary Market Frictions Mechanism

A second reason TRID-affected mortgages become less attractive to lenders is the increased difficulty in selling these loans in the secondary market. To assess this potential effect, we examine whether closed-end mortgages are associated with a relative decrease in the probability of sale in the secondary market. We estimate the following regression on the sample of originated mortgages, which are a subset of approved mortgages and therefore a smaller sample than the sample of approved and denied applications used in our main tests:

$$\begin{aligned} LoanSale_{i,j,t} = {} & \beta_1 Post_t \times Closed_{i,j,t} + \beta_2 Closed_{i,j,t} + \delta Applicant\_Characteristics_{i,j,t} \\ & + \theta Loan\_Controls_{i,j,t} + \gamma\beta_{i,t} Bank\_Controls_{i,t-1} \\ & + \Sigma\alpha_i Bank_i + \Sigma\alpha_{k,t} County\text{-}Year_{k,t} + \epsilon_{i,j,t}. \end{aligned} \tag{4}$$

The dependent variable is $LoanSale$, an indicator variable set equal to one if bank i sells loan j to a

[15] Although RateWatch also surveys fee-related information, this information is more sparsely populated.

non-affiliated institution, and zero otherwise. Panel A of Table 1 indicates that approximately 60.8% of originated loans are sold. All other variables are described in Section 3.2. If secondary market frictions associated with closed-end loans hinder their sale to a greater extent in the post-TRID period, we expect a negative and significant β_1.

Table 4 reports the results of estimating equation (4). Column (1) presents results with bank fixed effects and bank-year-level controls, while column (2) includes bank-year fixed effects. Both columns include application-level controls and county-year fixed effects. We document a negative and significant coefficient on $Post \times Closed$ in both columns, which indicates that the probability of selling an originated closed-end loan decreases to a greater extent in the post-TRID period relative to the equivalent change for originated open-end loans. This finding is consistent with secondary market frictions hindering the sale of closed-end loans and provides another reason that these loans are less attractive to lenders post-TRID. In sum, the results of Section 5.1 and Section 5.2 provide evidence of the mechanisms through which TRID-affected mortgages become relatively less attractive to banks post-TRID.

5.3 Small Business Lending

An additional consequence of TRID-affected loans becoming less attractive to banks is that they may redirect their funds to different lending opportunities that are unaffected by TRID. One such opportunity is small business lending. In accordance with the Community Reinvestment Act (CRA), banks are evaluated based on the collective amount of their home mortgage, small business, and small farm lending to low- and middle-income communities in the areas in which they operate. Prior literature finds that banks change their lending behavior to comply with the CRA (e.g., Agarwal et al., 2012; Ding et al., 2020). Therefore, banks can mitigate concerns regarding noncompliance with the CRA by increasing their small business lending.

Under the CRA, banks with total assets greater than $1 billion are required to disclose the aggregate number and amount of loans for each geography (defined as the county or tract) in which they originated or purchased small business or small farm loans. Thus, the CRA dataset provides bank-county-year level information regarding bank small business lending activity. We aggregate the HMDA application-level observations in our main sample to obtain the amount of mortgage lending at the bank-county-year level and merge these variables with the CRA dataset.

To assess whether small business lending changes following TRID, we estimate the following regression on banks with total assets greater than \$1 billion, where the unit of analysis is the bank-county-year:

$$\begin{aligned} SmBusLending_{i,k,t} = \; & \beta_1 Post_t \times Bank\_Closed\_Denied_{i,k,t} + \beta_2 Bank\_Closed\_Denied_{i,k,t} \\ & + \Sigma\alpha_i Bank\text{-}Year_{i,t} + \Sigma\alpha_{k,t} County\text{-}Year_{k,t} + \epsilon_{i,j,t}. \end{aligned} \tag{5}$$

The dependent variable *SmBusLending* is either *SmBusLoanAmount*, the log of the amount of small business loans originated in a particular bank-county-year, or *SmBusNumLoans*, the log of the number of small business loans originated in a particular bank-county-year. Both variables are constructed using information from the CRA dataset. *Bank_Closed_Denied* is the difference between the proportion of closed-end mortgage credit approved in a bank-county-year and the proportion of open-end mortgage credit approved in a bank-county-year, from our main sample. We then multiply this difference by -1 so that higher values of *Bank_Closed_Denied* correspond to a lower closed-end mortgage approval rate, relative to the open-end mortgage approval rate.[16] If banks compensate for reduced closed-end mortgage lending by directing funds toward other investment opportunities, particularly those that are also covered by the CRA, we expect a positive coefficient on *Post* × *Bank_Closed_Denied*. To account for bank-year-specific and county-year-specific factors, we also include bank-year and county-year fixed effects.

The results of estimating equation (5) are presented in Panel A of Table 5. Column (1) presents results using *SmBusLoanAmount* as the dependent variable, and column (2) presents results using *SmBusNumLoans* as the dependent variable. Across both columns, we find a positive and significant coefficient on *Post* × *Bank_Closed_Denied*. This finding indicates that, in counties in which TRID-affected mortgage lending is relatively low, banks appear to shift some funds toward small business lending in the same county. Overall, this test provides insight into how banks redirect their funds post-TRID and supports our argument that the attractiveness of TRID-affected mortgage lending decreases relative to other investment opportunities.

[16] To ensure that bank-counties are active in both the closed-end and open-end markets, we further restrict the sample to observations with non-zero approved closed-end and open-end mortgages.

5.4 Fintech Lending

A natural question we consider is whether other institutions compensate for the relative decrease in bank mortgage lending. We provide descriptive evidence into this question by examining whether fintech lenders, defined as institutions that have a complete end-to-end online mortgage application and approval process (Fuster et al., 2019), change their mortgage lending following TRID. Prior research argues that, relative to traditional lenders, fintech lenders can adjust credit supply more elastically in response to changes in credit demand (Fuster et al., 2019). Although fintechs are also subject to TRID, they may be subject to less regulatory oversight compared to commercial banks. As a result, fintech lenders may increase their mortgage lending in counties where banks reduce their TRID lending. However, we may not observe that fintechs compensate for lower bank mortgage lending since they are also subject to TRID.

To examine whether fintechs change their lending following TRID, we estimate the following regression, where the unit of analysis is the fintech-county-year:

$$\begin{aligned} Fintech\_Approved_{i,k,t} = \; & \beta_1 Post_t \times AvgBank\_Closed\_Denied_{k,t} + \beta_2 AvgBank\_Closed\_Denied_{k,t} \\ & + \Sigma\alpha_i Lender_i + \Sigma\alpha_t Year_t + \Sigma\alpha_k County_k + \epsilon_{i,j,t}. \end{aligned} \tag{6}$$

The dependent variable is $FinTech\_Approved$, which is the amount of credit extended by fintechs scaled by total applied-for credit. This measure does not distinguish between closed-end and open-end credit, because fintechs (and nonbanks, more generally) rarely extend open-end credit. The independent variable of interest ($AvgBank\_Closed\_Denied$) is defined at the county-year level as the average of $Bank\_Closed\_Denied$ for for all banks in each county-year. If fintechs at least partially compensate for reduced closed-end mortgage lending by banks, we expect a positive coefficient on $Post \times AvgBank\_Closed\_Denied$. We include lender fixed effects, year fixed effects and county fixed effects to account for unobservable characteristics specific to each lender, year, and county. In an additional specification, we replace the lender and year fixed effects with lender-year fixed effects. Given that our independent variable of interest is defined at the county-year level, we are unable to include county-year fixed effects. We cluster standard errors by county for this test, to ensure an appropriate minimum number of clusters (Petersen, 2009).

The results of estimating equation (6) are presented in Table 5, Panel B. Column (1) presents results with the baselines specification, while column (2) replaces the lender and year fixed effects with lender-year fixed effects. Across both columns, we find a positive and significant coefficient on $Post \times AvgBank\_Closed\_Denied$. This finding suggests that, post-TRID, fintechs approve a greater proportion of credit in counties where banks reduce their relative closed-end mortgage lending to a greater extent. While descriptive in nature, this tests provides some insight into whether other institutions at least partially compensate for lower mortgage lending by banks following TRID.

6 Supplemental Analyses

This section presents results of several analyses that investigate aggregate market effects and address alternative explanations for our main result of reduced post-TRID mortgage application approval at banks.

6.1 Aggregate market effects

We investigate aggregate market effects of lending changes following TRID by examining the total demand for closed-end credit and total approved closed-end credit.

Although conducting our main tests of mortgage approval at the application-level has several advantages, it is subject to an alternative explanation related to consumers' application choices. It is possible that consumers' reduced costs of processing disclosures motivates them to submit more complete applications to banks, thereby increasing demand for closed-end mortgages. In this case, the reduced approval probability we document could be attributed to an increase in applications submitted and therefore may not reflect reduced credit supply by banks. We also explore aggregate changes in demand and approved closed-end credit by expanding our sample to include all lenders.

To address these questions, we aggregate the amount of credit demanded and the amount of credit extended at the application-level to the county-year-*Closed* level and assess whether the total demand for and approved closed-end mortgages changes relative to the equivalent change for open-end mortgages. We estimate the following regression:

$$TotalLoans_{c,k,t} = \beta_1 Post_t \times Closed_{c,k,t} + \beta_2 Closed_{c,k,t} + \Sigma\alpha_{k,t} County\text{-}Year_{k,t} + \epsilon_{c,k,t}, \qquad (7)$$

where c indexes the closed-end status of the loans, k indexes the property county, and t indexes the year. The dependent variable $TotalLoans$ is either $NumCompleteApplic$, the log of the total number of complete mortgage applications that were not withdrawn (i.e., demand), or $NumApprovedLoans$, the log of the total number of approved mortgages. If the total credit demanded or extended increases (decreases) following the effective date of TRID, we expect a positive (negative) coefficient on $Post \times Closed$.

Table 6 presents results of estimating equation (7). We first focus on loans at banks only in columns (1) and (2). We present results for the dependent variable $NumCompleteApplic$ in column (1) and $NumApprovedLoans$ in column (2). We document a negative and significant coefficient on the interaction term $Post \times Closed$ in both columns. These results suggest that demand for closed-end credit from banks decreases relative to demand for open-end credit from banks following the effective date of TRID. Similarly, the total amount of closed-end credit approved by banks decreases relative to the total amount of open-end credit approved. These findings mitigate concerns that our mortgage approval probability results for banks are fully explained by an increase in the number of submitted applications at banks.

To investigate aggregate market effects, we expand our analysis to include all loans at all lenders. We present results for the dependent variable $NumCompleteApplic$ in column (3) and $NumApprovedLoans$ in column (4). In both columns, we document a positive and significant coefficient on the interaction term $Post \times Closed$. In contrast to the results restricted to commercial banks only, and consistent with simplified disclosures motivating consumers to apply for closed-end credit, the total demand for closed-end credit from all lenders increases. Consistent with our finding that fintechs absorb some of the unmet demand, the total amount of approved closed-end credit from all lenders increases. The combination of these results is consistent with consumers increasing their demand in total but shifting demand from banks to nonbanks. These results are also consistent with increased total demand being largely met at non-depository institutions.

6.2 Potential Selection Issue: Applicants Stopping Application Process

Another potential alternative explanation is related to a selection issue. Consumers' reduced costs of processing disclosures could motivate them to withdraw all applications or leave all applications incomplete (i.e., after receiving the Loan Estimate) in the post-TRID period. These consumers would not appear in our main sample of approved and denied applications. If they would have been approved had they continued the application process for any lender, this selection issue could mechanically reduce the approval probability and explain our main results.

To investigate whether this selection issue could fully explain our main results, we perform a sensitivity test where we classify varying percentages of the post-TRID $NoDecision$ closed-end applications as approved. This classification makes the conservative assumption that each incremental post-TRID $NoDecision$ closed-end application would have been approved had the applicant continued with the application process. By doing so, we can determine the percentage of the incremental applications that would need to have been approved in order for our primary inference to be overturned. In Table 7, we present the results of classifying 0%, 10%, 25%, 50%, 75%, 90%, and 100% of the post-period $NoDecision$ closed-end applications as approved. As expected, the magnitude of the coefficient on $Post \times Closed$ decreases as more applications are classified as approved. For example, with 10% of the incremental applications classified as approved, the coefficient corresponds to a 4.7 percentage point decrease in approval probability, compared to a 5.1 percentage point decrease under the benchmark case assuming no selection issue. Importantly, even with 75% of the $NoDecision$ applications classified as approved, we find a negative and marginally significant coefficient on $Post \times Closed$. Thus, the selection issue would have to be quite large in order to explain our results. To fully explain our results, between 75% and 90% of the applications that drop out of the mortgage process after engaging in comparison shopping would have to have completed the application process and have been approved absent TRID.

6.3 Additional Alternative Explanations

Our sample period includes the decade following the 2007 - 2009 financial crisis, which raises potential concerns that events other than the TRID rule drive our findings. Importantly, to explain our results, changes would need to be contemporaneous to TRID and differentially affect our treatment and control applications within a bank-year. In this section, we investigate two specific alternative explanations that would meet these criteria. First, the Qualified Mortgage Rule and Appraisals for Higher-Priced Mortgages Rule under Regulation Z, implemented in 2014, requires lenders to provide more information regarding appraisals to borrowers of "higher-risk" closed-end mortgages. Second, new securitization risk retention rules that became effective in 2015 require sellers of asset-backed securities to retain risk for mortgages that do not meet the definition of "qualified residential mortgage" (mostly closed-end mortgages).[17]

To investigate these alternative explanations, we estimate equation (1) after removing applications which are most affected by each of these other rules. For parsimony, we report results for specifications including both bank-year and county-year fixed effects. If the Qualified Mortgage Rule and related changes drive our results, we would not expect to document similar results after removing applications from higher risk borrowers. Therefore, we remove applications with a $Loan\_to\_Income$ ratio in the top quartile of each year's distribution. The results are presented in column (1) of Table 8. If the securitization risk rules drive our results, we would not expect to find results after removing applications submitted to banks with a large retained interest in sold mortgages. We classify banks as having a large retained interest if they are in the top quartile of retained interests in mortgages, measured during the pre-period. The results are presented in column (2) of Table 8. Across both columns, we continue to document a negative and significant coefficient on $Post \times Closed$, mitigating concerns that our results are driven by the above alternative explanations.

7 Conclusion

We document potential consequences of a rule designed to improve consumers' ability to process disclosures. The rule requires simplified borrower mortgage disclosures and should make affected mortgage loans less attractive to banks for two reasons. First, the rule should improve borrowers' ability to understand mortgage disclosures and constrain high interest rates and fees charged by banks. Second, the new disclosures are associated with increased secondary market frictions.

Our primary finding is that mortgage applications affected by TRID are associated with reduced approval probabilities following the effective date of TRID. We find evidence consistent with a reduction in borrowers' information processing costs and an increase in lenders' secondary market frictions. These findings suggest that both effects play a role in reducing the relative attractiveness of TRID-affected mortgages. We also find that banks partially compensate for lower mortgage

[17] The results in Table 4 are inconsistent with this explanation. Specifically, if this rule explains our results, we would expect the likelihood of loan sales of closed-end mortgages to *increase* given that the new rule does not require lenders to retain risk for closed-end mortgages. Instead, we find that the likelihood of closed-end loan sales decreases.

lending by increasing small business lending. Fintech lenders, which may be able to adjust credit more elastically and subject to less regulatory oversight, absorb some of the unmet demand in counties with reduced TRID-affected mortgage credit from banks. Collectively, these results provide additional evidence regarding the consequences of the rule and should be of interest to regulators such as the CFPB, which is charged with oversight of consumer protection.

Our paper makes several contributions. We contribute to the literature on information processing costs by documenting that regulations designed to benefit consumers can have consequences for the firms that internalize the costs of these regulations. We also contribute a complementary perspective to the literature on lending market transparency by focusing on disclosure to *borrowers*. Finally, our results indicate that banks' concerns about TRID violations and secondary market sales may have merit. Our findings should be of interest to regulators evaluating the effectiveness and broader consequences of TRID.

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Appendix A. Variable Definitions

Variable	Definition	Data Source
ApplicIncome	log of applicant income (in thousands).	HMDA
Approval	indicator variable set equal to one if the mortgage loan is approved and zero if the loan is denied. A mortgage loan is approved if it is either approved & originated or approved & not originated (see Appendix B).	HMDA
AvgBank_Closed_Denied	Average of *Bank_Closed_Denied* for all banks in a county-year.	HMDA
Bank_Closed_Denied	The difference between the approval rate of closed-end mortgages in a bank-county-year and the approval rate of open-end mortgages in the same bank-county-year. We multiply this difference by -1 to facilitate interpretation of this variable such that higher values correspond to greater reductions in TRID-affected mortgage approval.	HMDA
BankSize	log of total assets (in millions).	Call Report
Black	indicator variable set equal to one if the applicant is Black and zero otherwise.	HMDA
Closed	indicator variable set equal to one if the mortgage loan is a closed-end mortgage based on our CART classification and zero otherwise.	HMDA
ClosedRW	indicator variable set equal to one if the observation captures closed-end mortgage rates and zero if the observation captures open-end mortgage rates.	RateWatch
Conventional	indicator variable set equal to one if the mortgage loan is a conventional mortgage and zero otherwise. Conventional loans are any loans other than Federal Housing Administration-insured, Veterans Administration-guaranteed, or Farm Service Agency or Rural Housing Service loans.	HMDA
CoreDepositGrowth	log of the ratio of core deposits at the end of the year divided by core deposits at the end of the prior year.	Call Report
DepositIntRate	ratio of deposit interest expense to total deposits.	Call Report
Female	indicator variable set equal to one if the applicant is female and zero otherwise.	HMDA
Fintech_Approved	The mortgage approval rate in a fintech-county-year.	HMDA
Hispanic	indicator variable set equal to one if the applicant is Hispanic or Latino and zero otherwise.	HMDA
InterestRate	log of the average interest rate offered on either a closed-end or open-end mortgage for a given bank-county-year.	RateWatch
Loan_to_Income	log of the ratio of the loan amount to applicant income.	HMDA
LoanAmount	log of the loan amount (in thousands).	HMDA
LoanSale	indicator variable set equal to one if the originated loan is sold to a non-affiliated institution and zero otherwise.	HMDA
NoDecision	indicator variable set equal to one if the mortgage loan application does not have a decision (i.e., it is incomplete or withdrawn) and zero otherwise.	HMDA
NonInterestIncome	ratio of noninterest income to total assets.	Call Report
NPL	non-performing loans (the sum of nonaccrual loans and loans at least 90 days past due and still accruing) scaled by total loans.	Call Report
NumApprovedLoans	log of the number of total closed-end or open-end mortgage loans approved in a county-year, approved by either banks only or all lenders.	HMDA
NumCompleteApplic	log of the number of total closed-end or open-end mortgage complete applications (i.e., neither incomplete nor withdrawn) in a county-year, submitted to either banks only or all lenders.	HMDA
OwnerOccupied	indicator variable set equal to one if the mortgage is for a unit that is owner occupied as a principal dwelling and zero otherwise.	HMDA
Post	indicator variable set equal to one if the application was submitted in 2016 - 2019 and zero if the application was submitted in 2011 - 2014.	
Refinance	indicator variable set equal to one if the application purpose is refinancing and zero if the application purpose is home purchase.	
ROA	return on assets, calculated as net income divided by total assets.	Call Report
Securities	the sum of held-to-maturity, available-for-sale, and trading securities, scaled by total assets.	Call Report
SmBusLoanAmount	log of small business lending originated in a bank-county-year.	CRA
SmBusNumLoans	log of the number of small business loans originated in a bank-county-year.	CRA
*Tier*1	ratio of Tier 1 capital to risk-weighted assets.	Call Report
WSFgrowth	wholesale funding growth, defined as the change in wholesale funding (non-core deposits, subordinated debt and debentures, federal funds purchased, repos, and other borrowed money) during the year scaled by prior year wholesale funding.	Call Report

Appendix B. Summary of Samples

This table presents a summary of the outcome variable and unit of analysis for each of our tests. For tests conducted at the application-level, the table also indicates which HMDA action groups are included in the sample for analysis. All outcome variables are defined in Appendix A.

			Sample of Applications Included				
			Applications with Decision			Applications without Decision	
Table	**Outcome Variable**	**Unit of Analysis**	**Approved & Originated**	**Approved & Not Originated**	**Denied**	**Withdrawn**	**Incomplete**
Table 2	*Approval*	Application	✓	✓	✓		
Table 3, Panel A	*NoDecision*	Application	✓	✓	✓	✓	✓
Table 3, Panel B	*InterestRate*	Bank-county-year-*Closed*			N/A		
Table 4	*LoanSale*	Application	✓				
Table 5, Panel A	*SmBusLending*	Bank-county-year			N/A		
Table 5, Panel B	*Fintech_Approved*	Fintech-county-year			N/A		
Table 6	*TotalLoans*	County-year-*Closed*			N/A		
Table 7	*Approval*	Application	✓	✓	✓	(some)	(some)
Table 8	*Approval*	Application	✓	✓	✓		

Appendix C. Description of CART Classification

TRID applies to closed-end mortgage loan applications only. Our analyses rely on identifying closed-end mortgage applications (i.e., those subject to TRID) and open-end mortgage applications (i.e., those exempt from TRID). The HMDA data only identify whether an application is for a closed-end or open-end mortgage beginning in 2018. However, we are able to use other characteristics of each loan to classify mortgages in the 2011-2017 data as closed-end or open-end.

At a high level, our classification process assigns observations as closed-end or open-end based on the most likely classification from the input data. We perform the classification separately for refinancing loans and home purchase loans. For each loan type, we randomly select 67% of the 2018-2019 HMDA applications as our training sample, which contains the true *Closed* vs. *Open* classifications. Using this training sample, we train a Classification and Regression Tree (CART) that assigns each application as a closed-end or open-end mortgage based on the "true" closed-end indicator variable reported in the HMDA dataset. CART is a non-parametric estimation method that recursively splits decision trees based on the splits that achieve the lowest squared error between the predicted and actual classifications. CART allows for interactions and nonlinearities between all explanatory variables, which makes this method especially useful as we do not know the functional form of the relation between a loan's closed-end status and other loan characteristics. CART does not constrain the classification to any specific functional form.

We randomly select 50% of the training sample for cross-validation to tune hyper-parameters, where a 10-fold cross-validation is applied. The selected tree is the tree with the best complexity level *cp* according to the "One Standard Error Rule" based on the cross-validation error and cross-validation standard deviation of different tree models generated by the algorithm. We then use the trained model to assign as closed-end or open-end the remaining 33% of the 2018-2019 data (i.e., the "test" sample, with which we can calculate out-of-sample prediction performance because we have the true closed-end indicator for these applications).

Table C1 presents out-of-sample performance values and other summary information about CART. We retain all applications for which the $ActionTaken$ is originated, approved but not accepted, denied, withdrawn, or incomplete. The sample sizes of the training sample, the test sample, and the total sample are presented in the table. It is worth noting that the total numbers of observations in our sample in Table C1 are larger relative to those used in our main tests. The difference in sample size results from several sample restrictions imposed before conducting our main tests as discussed in Section 3.1. The explanatory variable with the highest importance in classifying the loans is an indicator that the loan is secured by a first lien, which is strongly associated with loans that are closed-end and less indicative of loans that are open-end. The table also shows that 86.93% of refinancing applications and 97.96% of home purchase applications are correctly classified in the training sample. The out-of-sample accuracy in the test sample is similar (86.91% and 97.97%, respectively). As the accuracy in the training sample is not significantly better than the accuracy in the test sample, we are not concerned about overfitting in our CART models.

Finally, we use all of the 2018-2019 HMDA applications to assign all refinancing and all home purchase applications, separately, as *Closed* or *Open*.

Table C1: Summary of CART and out-of-sample performance

This table provides details about the *Closed* vs. *Open* classification of our sample loan applications, using a Classification and Regression Trees (CART) model. We use separate CART models on the refinancing loans and home purchase loans. We randomly select 67% of the 2018-2019 data, which contains true *Closed* vs. *Open* classifications, as the training sample. The remaining 33% is the test sample. $ActionTaken$ is a variable indicating the type of action taken on the loan application, such as approved and originated (1), approved but not originated (2), denied (3), withdrawn (4), or incomplete (5). $PurchaserType$ is a variable indicating whether the loan was not originated or sold in the calendar year, or if it was purchased by another institution, the type of institution purchasing the loan (e.g., Fannie Mae, Freddie Mac, commercial bank, affiliate institution, etc.). All other variables are defined in Appendix A of the main paper. The explanatory variables are those variables that the algorithm determines have the highest variable importance for classification, and the variable importance is in parentheses after the variable name. In the CART training and tuning process, the algorithm tries different tree structures with different complexity parameters (cp, a hyper-parameter which measures the tree complexity) and sets a threshold cp_{max} for the tree. Once the algorithm reaches cp_{max}, it stops generating more complex trees. We randomly select 50% of the training sample for cross-validation to tune hyper-parameters, where a 10-fold cross-validation is applied. The selected tree is the tree with the best complexity level cp according to the "One Standard Error Rule" based on the cross-validation error and cross-validation standard deviation of different tree models generated by the algorithm. We report the accuracy in classifying *Closed* and *Open* in the training sample. We report the following out-of-sample performance measures: out-of-sample accuracy in classifying *Closed* and *Open*, and the out-of-sample area under the receiver operating characteristics (ROC) curve (AUC).

	Refinancing Loans	Home Purchase Loans
Sample applications	$ActionTaken$ is 1, 2, 3, 4, or 5	$ActionTaken$ is 1, 2, 3, 4, or 5
Classes	*Closed* and *Open*	*Closed* and *Open*
Explanatory Variables (Variable Importance)	$FirstLien$ (85%), $LoanAmount$ (8%), $PurchaserType$ (7%)	$FirstLien$ (61%), $LoanAmount$ (26%), $PurchaserType$ (8%), $ApplicIncome$ (5%)
Observations in training sample (67% of 2018-2019 data)	2,524,521	2,938,348
Observations in test sample (33% of 2018-2019 data)	1,243,420	1,447,246
2018-2019 Observations	3,767,941	4,385,594
2011-2017 Observations	23,022,395	14,969,130
Total Observations	26,790,336	19,354,724
Parameters of selected tree from cross-validation		
cp	0.0006427606	0.0004037116
Cross-validation error	0.5714	0.5601
Cross-validation std. dev.	0.0013	0.0032
Training sample performance:		
% correctly classified in training sample	86.93%	97.96%
Out-of-sample performance:		
% correctly classified in test sample	86.91%	97.97%
AUC	0.7794	0.8009

Figure 1: Timeline of Disclosure Provision

This figure presents a timeline of the mortgage application and origination process. The simplified, integrated disclosures are in red boxes. First, the borrower applies for the mortgage loan. Then, within three days, the bank must provide the Loan Estimate. At least three days before closing, the bank provides the Closing Disclosure. Finally, the borrower signs and finalizes the mortgage.

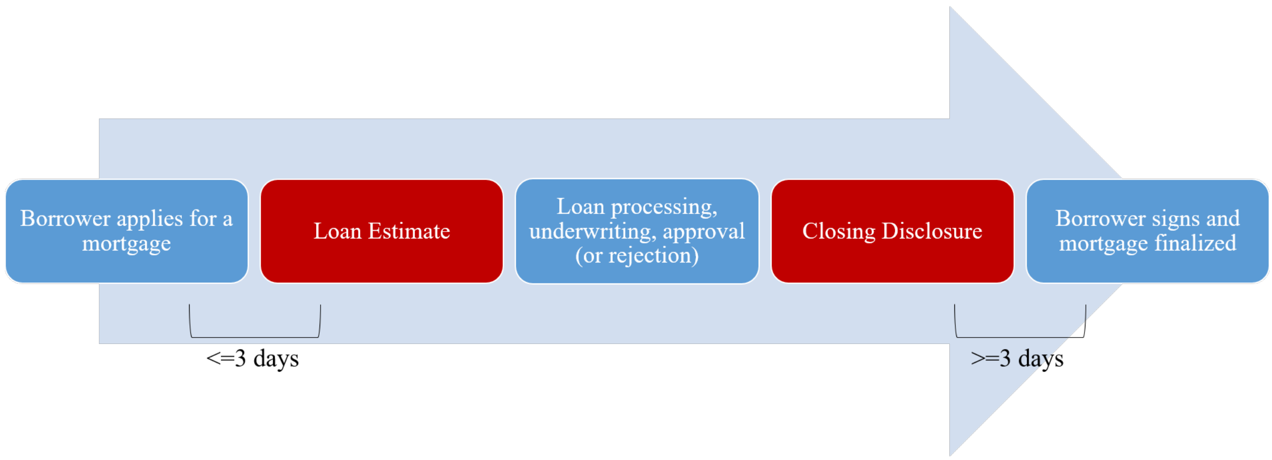

Figure 2: Illustrative Example of Old vs. New Disclosures

This figure presents an illustrative example of the old disclosures (top row) and the new TRID disclosures (bottom row, red dashed lines). Two of the old disclosures, the Good Faith Estimate and the initial TIL disclosure, were replaced by the Loan Estimate. The other two old disclosures, the HUD-1 Settlement Statement and the final TIL disclosure, were replaced by the Closing Disclosure. The source of the underlying graphic is https://www.consumerfinance.gov/policy-compliance/know-you-owe-mortgages/new-disclosures-streamline-process/ (accessed March 2021).

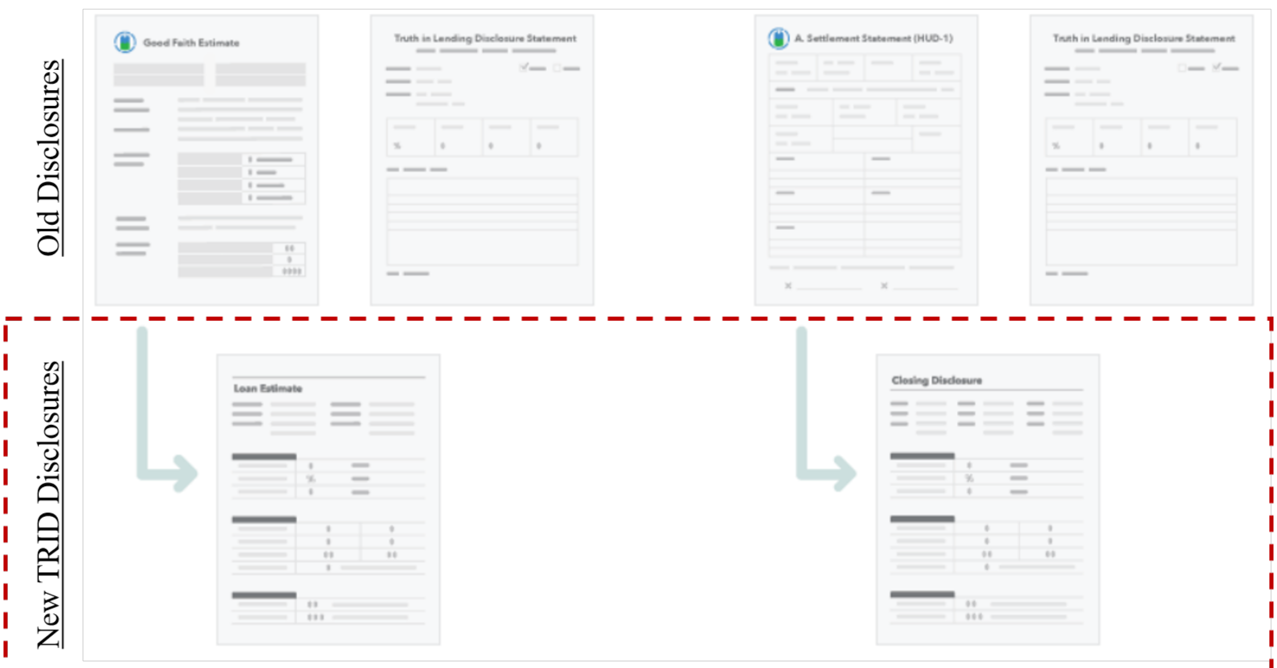

Figure 3: Excerpts from Hypothetical Disclosures

This figure presents excerpts of the new TRID disclosures and the old disclosures that they replaced, the Good Faith Estimate and HUD-1 Settlement Statement from HUD and the TIL disclosures. Panel A presents the format of the old Good Faith Estimate, regulated by HUD under RESPA, and provided to borrowers shortly after the bank receives the borrower's application. Panel B presents the format of the old HUD-1 Settlement Statement, regulated by HUD under RESPA, and provided to borrowers shortly before closing. Panel C presents the format of the old TIL disclosures, regulated by TILA. The format is the same for the initial TIL disclosure and the final TIL disclosure. Panel D presents the format of the new simplified TRID disclosures. The format is the same for the two TRID disclosures, the Loan Estimate and the Closing Disclosure. All hypothetical disclosures are for a loan of $162,000 and excerpted from Kleimann (2013).

Panel A: Good Faith Estimate (Old HUD Disclosure)

Your initial loan amount is	$ 162,000.00
Your loan term is	30 years
Your initial interest rate is	3.875 %
Your initial monthly amount owed for principal, interest, and any mortgage insurance is	$ 844.13 per month
Can your interest rate rise?	☒ No ☐ Yes, it can rise to a maximum of %. The first change will be in
Even if you make payments on time, can your loan balance rise?	☒ No ☐ Yes, it can rise to a maximum of $
Even if you make payments on time, can your monthly amount owed for principal, interest, and any mortgage insurance rise?	☒ No ☐ Yes, the first increase can be in and the monthly amount owed can rise to $. The maximum it can ever rise to is $.
Does your loan have a prepayment penalty?	☐ No ☒ Yes, your maximum prepayment penalty is $ 3,240.00
Does your loan have a balloon payment?	☒ No ☐ Yes, you have a balloon payment of $ due in years.

Some lenders require an escrow account to hold funds for paying property taxes or other property-related charges in addition to your monthly amount owed of $ 844.13 .
Do we require you to have an escrow account for your loan?
☐ No, you do not have an escrow account. You must pay these charges directly when due.
☒ Yes, you have an escrow account. It may or may not cover all of these charges. Ask us.

Panel B: HUD-1 Settlement Statement (Old HUD Disclosure)

J. Summary of Borrower's Transaction

100. Gross Amount Due from Borrower	
101. Contract sales price	$180,000.00
102. Personal property	
103. Settlement charges to borrower (line 1400)	$9,437.30
104. HOA Capital Contribution to HOA Acre Inc	$500.00
105. HOA Processing Fee to HOA Acre Inc	$150.00
Adjustment for items paid by seller in advance	
106. City/town taxes to	
107. County taxes to	
108. Assessments to	
109. HOA Dues 04/15/2013 to 04/30/2013	$80.00
110.	
111.	
112.	
120. Gross Amount Due from Borrower	$190,167.30
200. Amount Paid by or in Behalf of Borrower	
201. Deposit or earnest money	$10,000.00
202. Principal amount of new loan(s)	$162,000.00
203. Existing loan(s) taken subject to	
204. Seller Credit	$2,500.00
205. Rebate from Epsilon Title	$750.00
206. Appraisal Fee Credit Maple Bank	$405.00
207.	
208.	
209.	
Adjustments for items unpaid by seller	
210. City/town taxes 01/01/2013 to 04/14/2013	$365.04
211. County taxes to	
212. Assessments to	
213.	
214.	
215.	
216.	
217.	
218.	
219.	
220. Total Paid by/for Borrower	$176,020.04
300. Cash at Settlement from/to Borrower	
301. Gross amount due from borrower (line 120)	$190,167.30
302. Less amounts paid by/for borrower (line 220)	($176,020.04)
303. Cash ☒ **From** ☐ **To Borrower**	$14,147.26

Panel C: TIL Disclosures (Old)

Annual Percentage Rate The cost of your credit as a yearly rate.	Finance Charge The dollar amount the credit will cost you assuming the annual percentage rate does not change.	Amount Financed The amount of credit provided to you or on your behalf as of loan closing.	Total of Payments The amount you will have paid after you have made all payments as scheduled assuming the annual percentage rate does not change.
4.174%	**$118,830.27**	$162,000.00	$355,037.07

You have the right to receive at this time an itemization of the Amount Financed.

☐ I want an itemization. ☐ I do not want an itemization.

INTEREST RATE AND PAYMENT SUMMARY

	Rate & Monthly Payment
Interest Rate	3.875%
Principal and Interest	$761.78
Est. Taxes + Insurance (Escrow) • Includes Private Mortgage Insurance	$288.48
Total Est. Monthly Payment	**$1,050.26**

Panel D: Simplified TRID Disclosures (New)

Loan Terms		Can this amount increase after closing?
Loan Amount	$162,000	**NO**
Interest Rate	3.875%	**NO**
Monthly Principal & Interest *See Projected Payments below for your Estimated Total Monthly Payment*	$761.78	**NO**
		Does the loan have these features?
Prepayment Penalty		**YES** • **As high as $3,240** if you pay off the loan during the first 2 years
Balloon Payment		**NO**

Projected Payments		
Payment Calculation	**Years 1-7**	**Years 8-30**
Principal & Interest	$761.78	$761.78
Mortgage Insurance	+ 82	+ —
Estimated Escrow *Amount can increase over time*	+ 206	+ 206
Estimated Total Monthly Payment	$1,050	$968

Estimated Taxes, Insurance & Assessments *Amount can increase over time*	$206 a month	**This estimate includes** ☒ Property Taxes ☒ Homeowner's Insurance ☐ Other: *See Section G on page 2 for escrowed property costs. You must pay for other property costs separately.*	**In escrow?** **YES** **YES**

Figure 4: Coefficient plot - analysis of changes in the probability of mortgage approval

This figure plots coefficient estimates of $Year \times Closed$ from an entropy-balance-weighted DiD regression where the dependent variable is an indicator variable set equal to one if the mortgage loan is approved and zero if the loan is denied (*Approval*). Coefficient estimates are presented relative to the last pre-TRID period, year 2014. The regression includes bank-year and county-year fixed effects and all *Applicant_Characteristics* and *Application_Controls* included in the main regressions. The shaded areas around the coefficients reflect the 95% confidence intervals. Standard errors are clustered by bank and county-year.

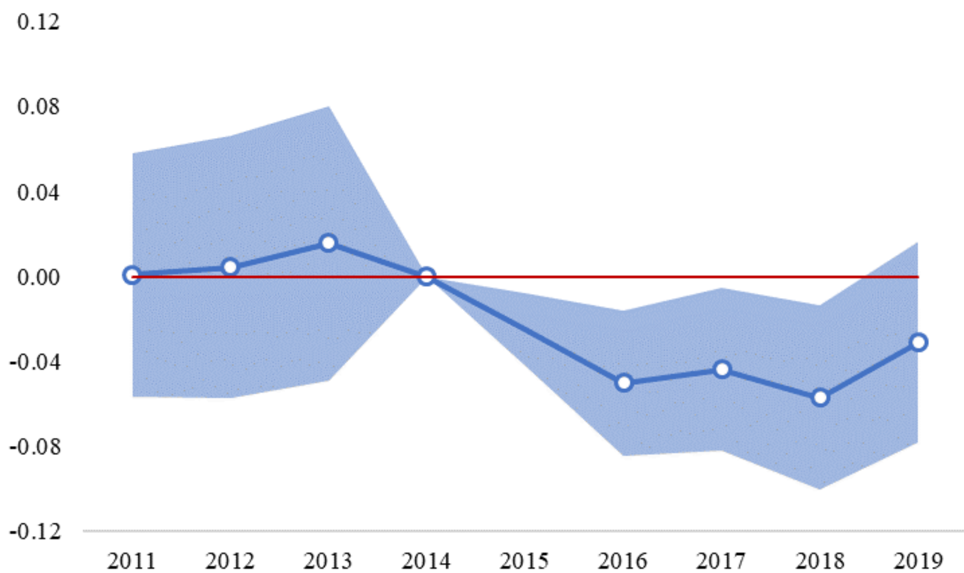

Table 1: Descriptive statistics

This table presents descriptive statistics for our sample. All logged variables are presented unlogged in Panel A and Panel C of this table. Continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in Appendix A. Panel A presents descriptive statistics of application-level and bank-year-level variables for the full sample. Panel B presents descriptive statistics of applicant characteristics for closed-end vs. open-end loans in our sample. We present descriptive statistics for the open-end sample before and after weighting observations based on entropy balancing. Panel C presents descriptive statistics of loan characteristics for closed-end vs. open-end loans in our sample.

Panel A: Full Sample

	N	Mean	Std Dev	P25	Median	P75
Outcome variables (application-level)						
Approval	19,455,329	0.796	0.403	1.000	1.000	1.000
NoDecision	22,250,066	0.126	0.331	0.000	0.000	0.000
LoanSale	14,705,779	0.608	0.488	0.000	1.000	1.000
Test variables (application-level)						
Closed	19,455,329	0.954	0.210	1.000	1.000	1.000
Post	19,455,329	0.389	0.488	0.000	0.000	1.000
Applicant characteristics (application-level)						
Female	19,455,329	0.287	0.452	0.000	0.000	1.000
Hispanic	19,455,329	0.079	0.270	0.000	0.000	0.000
Black	19,455,329	0.140	0.347	0.000	0.000	0.000
ApplicIncome	19,455,329	121.627	119.672	53.000	86.000	142.000
Loan controls (application-level)						
LoanAmount	19,455,329	235.780	216.678	105.000	170.000	285.000
Conventional	19,455,329	0.891	0.311	1.000	1.000	1.000
OwnerOccupied	19,455,329	0.875	0.331	1.000	1.000	1.000
Refinance	19,455,329	0.622	0.485	0.000	1.000	1.000
Bank controls (bank-year-level)						
BankSize	7,359	11,055,027	108,153,477	282,875	521,408	1,112,179
Tier1Capital	7,359	0.153	0.043	0.122	0.141	0.172
Securities	7,359	0.195	0.112	0.108	0.183	0.269
NonInterestIncome	7,359	0.011	0.015	0.005	0.008	0.011
ROA	7,359	0.011	0.007	0.007	0.011	0.014
DepositInterestRate	7,359	0.006	0.003	0.004	0.005	0.008
NPL	7,359	0.016	0.019	0.005	0.01	0.02
CoreDepositGrowth	7,359	0.043	0.119	-0.012	0.02	0.061
WSFgrowth	7,359	0.098	0.191	-0.012	0.075	0.174

Panel B: Entropy Balancing Statistics for Applicant Characteristics

	Closed-End			Open-End					
				Pre-Balancing			Post-Balancing		
Variable	**Mean**	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**	**Mean**	**Variance**	**Skewness**
Female	0.286	0.204	0.946	0.300	0.210	0.872	0.286	0.204	0.946
Hispanic	0.080	0.073	3.108	0.071	0.066	3.345	0.080	0.073	3.109
Black	0.141	0.121	2.070	0.127	0.111	2.247	0.140	0.121	2.071
ApplicIncome	4.506	0.554	0.364	4.532	0.538	0.293	4.506	0.554	0.363

Panel C: Comparison of Loan Controls for Treatment and Control Samples

	Closed-end		Open-end	
	Mean	Std Dev	Mean	Std Dev
LoanAmount	241.825	218.872	110.546	103.481
Conventional	0.887	0.317	0.986	0.117
OwnerOccupied	0.873	0.333	0.930	0.256
Refinance	0.610	0.488	0.886	0.318

Table 2: Analysis of changes in the probability of mortgage approval

This table presents the results of entropy-balance-weighted regressions where the dependent variable is an indicator variable set equal to one if the mortgage loan is approved and zero if the loan is denied (*Approval*). The sample includes approved and denied mortgage loan applications. *Post* is subsumed by bank-year and/or county-year fixed effects. t-statistics are in parentheses. Standard errors are clustered by bank and county-year. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Dependent Variable:	*Approval*	
Model:	(1)	(2)
$Post \times Closed$	-0.055***	-0.051***
	(-3.49)	(-3.28)
$Closed$	0.272***	0.270***
	(7.27)	(6.99)
$BankSize$	-0.009	
	(-0.20)	
$Tier1$	-0.063	
	(-0.13)	
$Securities$	-0.305**	
	(-2.12)	
$NonInterestIncome$	0.742	
	(0.94)	
ROA	-0.355	
	(-0.25)	
$DepositIntRate$	5.000	
	(1.41)	
NPL	0.562	
	(1.19)	
$CoreDepositGrowth$	0.035	
	(1.49)	
$WSFgrowth$	0.040**	
	(2.41)	
$LoanAmount$	-0.047***	-0.046***
	(-13.37)	(-13.95)
$Conventional$	0.056***	0.057***
	(5.96)	(6.75)
$OwnerOccupied$	0.113***	0.112***
	(9.92)	(9.86)
$Refinance$	-0.059***	-0.058***
	(-4.62)	(-4.57)
$Female$	-0.006***	-0.005**
	(-2.63)	(-2.34)
$Hispanic$	-0.082***	-0.080***
	(-18.04)	(-18.04)
$Black$	-0.091***	-0.090***
	(-21.15)	(-21.63)
$ApplicIncome$	0.127***	0.125***
	(20.29)	(19.93)
Observations	19,455,329	19,455,329
Adj R-Squared	0.169	0.181
Bank FE	Yes	No
County-Year FE	Yes	Yes
Bank-Year FE	No	Yes

Table 3: Analysis of the role of changes in borrower information costs

Panel A presents the results of entropy-balance-weighted regressions where the dependent variable is an indicator variable set equal to one if the mortgage loan application is incomplete or withdrawn and zero if the loan is approved or denied ($NoDecision$). The sample includes approved, denied, incomplete, and withdrawn mortgage loan applications. Standard errors are clustered by bank and county-year. Panel B presents the results of OLS regressions where the dependent variable is the log of the average interest rate offered on either a closed-end or open-end mortgage ($InterestRate$). The sample includes observations from bank-county-years with available RateWatch interest rates in 2013-2014 and 2016-2017. Standard errors are clustered by bank and county-year. In both panels, $Post$ is subsumed by bank-year and/or county-year fixed effects, and t-statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Panel A: Comparison Shopping

Dependent Variable:	$NoDecision$	
Model:	(1)	(2)
$Post \times Closed$	0.049***	0.050***
	(4.43)	(4.04)
$Closed$	-0.065***	-0.067***
	(-5.39)	(-5.41)
$BankSize$	0.076***	
	(3.08)	
$Tier1$	0.609*	
	(1.83)	
$Securities$	-0.293**	
	(-2.29)	
$NonInterestIncome$	0.175	
	(0.30)	
ROA	-2.482***	
	(-2.93)	
$DepositIntRate$	-1.190	
	(-0.47)	
NPL	-1.060***	
	(-3.78)	
$CoreDepositGrowth$	-0.039**	
	(-1.99)	
$WSFgrowth$	-0.017*	
	(-1.81)	
$LoanAmount$	0.017***	0.016***
	(3.15)	(2.95)
$Conventional$	-0.049***	-0.048***
	(-5.98)	(-5.66)
$OwnerOccupied$	-0.025***	-0.024***
	(-5.21)	(-5.15)
$Refinance$	0.027***	0.027***
	(5.07)	(5.14)
$Female$	0.004***	0.004***
	(6.17)	(7.05)
$Hispanic$	0.011***	0.011***
	(3.01)	(2.84)
$Black$	0.012***	0.012***
	(10.36)	(9.92)
$ApplicIncome$	-0.008*	-0.007*
	(-1.91)	(-1.80)
Observations	22,250,066	22,250,066
Adj R-Squared	0.052	0.062
Bank FE	Yes	No
County-Year FE	Yes	Yes
Bank-Year FE	No	Yes

Panel B: Offered Interest Rates

Dependent Variable:	*InterestRate*	
Model:	(1)	(2)
$Post \times ClosedRW$	-0.140***	-0.128***
	(-4.95)	(-4.78)
$ClosedRW$	-0.191***	-0.199***
	(-2.97)	(-3.01)
Observations	28,020	28,005
Adj R-Squared	0.544	0.564
Bank FE	Yes	No
County-Year FE	Yes	Yes
Bank-Year FE	No	Yes

Table 4: Analysis of secondary market frictions: changes in the likelihood of loan sales

This table presents the results of entropy-balance-weighted regressions where the dependent variable is an indicator variable set equal to one if the mortgage loan is sold to a non-affiliated institution and zero otherwise (*LoanSale*). The sample includes originated mortgage loans. *Post* is subsumed by bank-year and/or county-year fixed effects. t-statistics are in parentheses. Standard errors are clustered by bank and county-year. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Dependent Variable:	*LoanSale*	
Model:	(1)	(2)
$Post \times Closed$	-0.100**	-0.102**
	(-2.44)	(-2.17)
Closed	0.590***	0.581***
	(8.64)	(8.20)
BankSize	0.045	
	(0.90)	
Tier1	-1.281***	
	(-2.73)	
Securities	0.015	
	(0.10)	
NonInterestIncome	2.923***	
	(3.70)	
ROA	-0.032	
	(-0.02)	
DepositIntRate	7.829	
	(1.22)	
NPL	1.669**	
	(2.20)	
CoreDepositGrowth	-0.016	
	(-0.35)	
WSFgrowth	0.033	
	(1.24)	
LoanAmount	-0.013	-0.012
	(-0.78)	(-0.72)
Conventional	-0.180***	-0.171***
	(-5.99)	(-5.95)
OwnerOccupied	0.004	0.005
	(0.43)	(0.50)
Refinance	0.021	0.022
	(1.34)	(1.47)
Female	-0.003	-0.002
	(-1.54)	(-1.14)
Hispanic	0.000	0.000
	(0.06)	(0.09)
Black	-0.005*	-0.006**
	(-1.94)	(-2.28)
ApplicIncome	-0.041***	-0.041***
	(-12.11)	(-12.71)
Observations	14,705,779	14,705,779
Adj R-Squared	0.574	0.593
Bank FE	Yes	No
County-Year FE	Yes	Yes
Bank-Year FE	No	Yes

Table 5: Analysis of shifts in lending

Panel A presents the results of OLS regressions where the dependent variable is the log of either the amount of small business lending originated in a bank-county-year (*SmBusLoanAmount*) or the number of small business loans originated in a bank-county-year (*SmBusNumLoans*). The sample includes bank-county-year observations with available CRA small business lending data. *Post* is subsumed by bank-year and county-year fixed effects. Standard errors are clustered by bank and county-year. Panel B presents the results of OLS regressions where the dependent variable is the proportion of approved credit relative to total applied-for credit in a lender-county-year ($Fintech\_Approved$). The sample includes fintech lenders only. *Post* is subsumed by year fixed effects or lender-year fixed effects. Standard errors are clustered by county. In both panels, *t*-statistics are in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Panel A: Small Business Lending

Dependent Variable:	*SmBusLoanAmount*	*SmBusNumLoans*
Model:	(1)	(2)
Post × *Bank_Closed_Denied*	0.334***	0.247***
	(3.29)	(3.07)
Bank_Closed_Denied	-1.214***	-1.050***
	(-11.91)	(-14.72)
Observations	48,479	48,479
Adj R-Squared	0.509	0.595
Bank-Year FE	Yes	Yes
County-Year FE	Yes	Yes

Panel B: Fintech Lending

Dependent Variable:	*Fintech_Approved*	
Model:	(1)	(2)
Post × *AvgBank_Closed_Denied*	0.092***	0.036***
	(8.72)	(3.48)
AvgBank_Closed_Denied	-0.051***	-0.016**
	(-6.08)	(-2.02)
Observations	46,014	46,014
Adj R-Squared	0.369	0.441
Lender FE	Yes	No
Year FE	Yes	No
Lender-Year FE	No	Yes
County FE	Yes	Yes

Table 6: Analysis of demand and aggregate mortgage lending

This table presents the results of OLS regressions where the dependent variable is the log of either the total number of complete closed-end or open-end mortgage applications submitted to lenders in a county-year (*NumCompleteApplic*) in columns (1) and (3) or the number of closed-end or open-end mortgages approved by lenders in a county-year (*NumApprovedLoans*) in columns (2) and (4). The sample is comprised of two observations per county-year, one where *Closed* = 1 and one where *Closed* = 0. Columns (1) and (2) aggregate loans at banks only, and columns (3) and (4) include all loans at all lenders (banks and nonbanks). *Post* is subsumed by county-year fixed effects. *t*-statistics are in parentheses. Standard errors are clustered by county-year. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Lenders included:	Banks only		All lenders	
Dependent Variable:	*NumCompleteApplic*	*NumApprovedLoans*	*NumCompleteApplic*	*NumApprovedLoans*
Model:	(1)	(2)	(3)	(4)
Post × *Closed*	-0.285***	-0.355***	0.125***	0.043***
	(-31.41)	(-33.82)	(14.27)	(4.29)
Closed	3.128***	3.375***	3.742***	3.981***
	(324.31)	(275.93)	(337.03)	(278.52)
Observations	41,890	41,890	41,902	41,902
Adj R-Squared	0.937	0.924	0.943	0.929
County-Year FE	Yes	Yes	Yes	Yes

Table 7: Sensitivity tests to address potential selection issue

This table presents tests to address the selection issue of a potential increase in applicants who do not proceed with applications at any institution (i.e., those who are not in the approved or denied group comprising our main sample) mechanically reducing the likelihood of approval. We assess the sensitivity of our results to varying magnitudes of this selection issue by classifying varying percentages of post-TRID closed-end *NoDecision* applications as approved. The table presents the results of entropy-balance-weighted regressions where the dependent variable is an indicator variable set equal to one if the mortgage loan is approved and zero if the loan is denied (*Approval*). The sample includes approved and denied mortgage loan applications and 0%, 10%, 25%, 50%, 75%, 90%, and 100% of the post-TRID closed-end *NoDecision* applications in columns (1), (2), (3), (4), (5), (6), and (7), respectively. *Post* is subsumed by bank-year and county-year fixed effects. All control variables are included in the regressions but suppressed from the output. t-statistics are in parentheses. Standard errors are clustered by bank and county-year. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Dependent Variable:				*Approval*			
NoDecision classified as approved:	0%	10%	25%	50%	75%	90%	100%
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post × *Closed*	-0.051***	-0.047***	-0.042***	-0.034**	-0.027*	-0.023	-0.020
	(-3.28)	(-3.05)	(-2.71)	(-2.19)	(-1.72)	(-1.45)	(-1.29)
Closed	0.270***	0.270***	0.271***	0.272***	0.272***	0.273***	0.273***
	(6.99)	(6.99)	(7.00)	(7.02)	(7.03)	(7.04)	(7.04)
Observations	19,455,329	19,581,182	19,769,957	20,084,558	20,399,106	20,587,804	20,713,584
Adj R-Squared	0.181	0.182	0.182	0.183	0.185	0.185	0.186
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Additional analyses

This table presents the results of entropy-balance-weighted regressions where the dependent variable is an indicator variable set to one if the mortgage loan is approved and zero if the loan is denied (*Approval*). We assess the robustness of our main results on mortgage approval to excluding various sets of applications. The sample in column (1) excludes applications with *Loan_to_Income* in the top quartile of each year. The sample in column (2) excludes applications submitted to banks with a retained interest in mortgages in the top quartile for all banks with securitized mortgages, with the retained interest and securitized mortgages measured in the 2011-2015 period. *Post* is subsumed by bank-year and county-year fixed effects. All control variables are included in the regressions but suppressed from the output. *t*-statistics are in parentheses. Standard errors are clustered by bank and county-year. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix A.

Dependent Variable:	*Approval*	
Sample observations excluded:	High-risk applications	Applications to banks with high pre-TRID securitized mortgage retained interest
Model:	(1)	(2)
Post × *Closed*	-0.061***	-0.050***
	(-3.72)	(-3.02)
Closed	0.250***	0.265***
	(6.15)	(6.39)
Observations	14,591,471	18,602,866
Adj R-Squared	0.164	0.181
Controls	Yes	Yes
County-Year FE	Yes	Yes
Bank-Year FE	Yes	Yes