Mortgage Credit Regulation based on Data Quality: Evidence from Automated Underwriting *

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Abstract

In this paper, I study the credit market outcomes and economic consequences of restrictions placed on algorithm based loan evaluations due to inaccurate statistical risk assessments resulting from a decline in data quality. I exploit an exogenous policy change in a major automated mortgage underwriting system which eliminated such restrictions placed on a subset of loan applicants. Utilizing novel data and a differences-in-differences strategy, I find that the policy change leads to an increase in mortgage credit access without any noticeable impact on credit risk. This change accounts for 26% of the increase in approval rates, with stronger effects where there is limited human interaction in the loan application process and where lenders have greater incentives for mortgage securitization. Further evidence suggests greater benefits to racial minorities and for borrowers facing financial frictions in availing alternate mortgage products due to lender litigation. While homeownership rates rise with spillover effects through lower rent growth in the more exposed areas, exposed banks end up crowding out commercial credit. My findings highlight the significance of automated mortgage underwriting for creditworthy and credit-constrained borrowers, which has important economic implications.

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1 Introduction

One of the most important aspects governing the allocation of credit in the mortgage market[1] is the mortgage underwriting procedure - a process through which lenders screen credit seeking loan applicants in order to evaluate the applicant's credit risk. While the substantial involvement of algorithm based automated systems in mortgage underwriting has brought about benefits such as reduced processing times, increased loan production capacity and consistency in underwriting (Foote et al., 2019; Talebzadeh et al., 1995), an increasingly data driven underwriting procedure means that the underlying applicant data is crucial in the statistical evaluation of borrowers and can have real consequences in the mortgage market. In this paper, I study how restrictions to automated underwriting due to inaccurate borrower data effects the efficiency in mortgage credit allocation. In particular, I examine the implications of eliminating such restrictions on the trade off between credit access and risk management, the effects on credit constrained borrowers and the real effects.

The effectiveness of statistical evaluation depends on the accuracy and quality of the underlying borrower data. Deterioration in data reporting practices in the period leading up to the financial crisis, especially in terms of misrepresentations (Griffin, 2021; Griffin & Maturana, 2016a) led to inaccurate borrower characteristics. A major underwriting system, Desktop Underwriter provided by the government sponsored entity Fannie Mae[2], had imposed undisclosed restricting factors in their algorithm in addition to standard risk assessments in their evaluation of certain loan applicants. This was done in order to compensate for the inability to form accurate risk assessment resulting from deteriorated data quality. Inaccurate data meant that it became difficult to correlate these borrower characteristics with subsequent loan performance to form accurate risk assessments.

During the update to Desktop Underwriter in July 2017, these previously undisclosed compensating factors were removed to allow for loans to be evaluated based solely on statistical risk assessment. The post crisis era marked a period of gradual improvement in borrower data quality

[1]The mortgage market is the largest consumer lending market in the U.S. Mortgages form the largest loan category on banks' balance sheets. Residential (1-4 and multi-family) mortgage accounts for 25% of banks' total loans (FDIC, 2022Q2). Mortgage loans are also the most important source of credit for U.S. households with a total balance of $11 trillion, comprising 71% of the total household debt (Federal Reserve Bank of New York, 2022).

[2]Desktop Underwriter is the largest automated underwriting system in terms of underwriting activity in the US. Close to 5 million conventional loan applications were underwritten through Desktop Underwriter in 2015

enabling better statistical risk assessments[3]. This event provides a unique setting and a plausibly exogenous shock to underwriting system evaluations to generate sudden variation in lending standards. It allows to quantify the effects of changes in underwriting policy in due cognizance of improved data quality. More importantly, it results in sudden, sharp variation in the evaluation standards for the same data inputs in a particular automated underwriting system, independent of other factors and enabling causal inferences. While tackling the challenge of identification is facilitated by the Desktop Underwriter software update, another challenge facing empirical researchers is measurement: There is a lack of public or readily obtainable data on the exact automated underwriting systems being utilized by mortgage lenders. I overcome this barrier by collecting confidential data on lenders' usage of the Desktop Underwriting system (DU) obtained from Fannie Mae.

I start my analysis with a descriptive approach. I utilize data maintained at Fannie Mae on all loan applications being run through their DU automated underwriting system in order to inspect their evaluation outcomes over time. The accuracy of many loan characteristics such as income and debt components had deteriorated in pre-crisis period. In addition, there was misreporting as borrower incomes were incorrectly calculated, overstated (Ambrose et al., 2016), falsified (W. Jiang et al., 2014) or not supported with underlying documentation and other liabilities such as second liens were not reported (Griffin & Maturana, 2016b). All of this contributed to the difficulty in accurately capturing a borrower's debt to income ratio. However, improvement in data quality in the years after the crisis has enabled more accurate measurements of debt and income components. I document that prior to the third quarter of 2017, only about half of all loan applications with debt-to-income ratios of over 45 received positive or approve recommendations. Such a pattern is non-existent for loan applications below debt-to-income ratio of 45 where the rate of approve recommendations is about double in comparison. However, starting from the third quarter of 2017, coinciding with the DU software update, positive recommendation rates from DU underwriting system for loan applications with debt-to-income higher than 45 jumped by about 40% and the overall rate of approve recommendations for this group of applicants became similar to all other loan applications. The aggregate trends are illustrative of the changes made in the DU software and shows how the update results in a positive shock to the recommendations for high

[3] The update also allowed a periodic re-estimation of their model risk assessments based on newer borrower data.

debt-to-income borrowers.

Motivated from this initial evidence of the recommendation patterns from Fannie Mae's data, I rely on this setting to explore how this shock to lending standards coming from changes to algorithm based recommendation effects the *extensive* margin of *overall* credit access through reliance on automated underwriting, i.e actual mortgage approval rates through plausibly exogenous change in recommendations from the software update. To this end, I first merge confidential data on DU underwriting system to publicly available data on the near universe of mortgage applications from Home Mortgage Disclosure Act (HMDA) based on information about identity of the lender and the county of operation. In particular, I use data on the yearly amount of loan applications submitted to the DU underwriting system by a given lender in a given county and map it to the corresponding activity for that lender and county pair in the HMDA. I then exploit regional variation on the fraction of loans underwritten through DU (that is the fraction of loans potentially subject to the DU update) at the county level as measure of treatment intensity. My difference in difference approach compares mortgage approvals, before and after the software update policy, across counties with varying levels of exposure prior to the shock to DU recommendations.

The main identifying assumption behind the difference in difference approach is that changes in mortgage approvals would have been the same across counties in the absence of this policy. Nonetheless, a major concern is that, as the extent of reliance on DU automated underwriting system across counties is not random, it may be that counties with differing reliance on DU may have different trends in mortgage approval rates. To alleviate such concerns, I plot a dynamic event study and show that mortgage approval rates did not diverge across counties with differing exposures to DU underwriting system before the software update policy. Moreover, county level reliance on DU underwriting system may be correlated with other county level characteristics. For this reason, I perform balance tests and control for several time varying county level factors in my estimations.

After assessing the validity of my empirical approach, I then proceed to estimate the effect of this shock to automated mortgage underwriting on overall mortgage approval rates. My baseline results suggests that, holding constant all other factors, a county entirely dependent on DU for automated mortgage underwriting experienced a 5 percentage point increase in overall mortgage approval rates after the shock to DU recommendations. This effect holds even after comparing two counties in the same state in the same year as well as accounting for time invariant county specific factors. Increasing exposure from the 25th percentile to 75th percentile in the distribution of DU dependence would increase mortgage approval rates by 1 percentage point. Such an estimated effect is a sizeable increase in approvals and represents about 1.40% increase of the approval rate for the average county prior to the shock to DU recommendations. Moreover, the estimates suggest an overall increase of 2.3 percentage point in mortgage approval rate based on pre-treatment market share of DU usage. Next, in order to support the baseline results, I validate that it is indeed the the removal of restricting factors in the recommendation of high debt-to-income borrowers, which is driving the increase in approval rates. I find that the increase in approval rates is much larger in counties which have a greater reliance on DU underwriting system and have a large share of affected debt-to-income applicants prior to the software update.

The baseline result on the extensive margin increase in credit access may not be valid if high and low DU dependent counties differ in other dimensions that would improve mortgage approvals after the 2017 shock to automated underwriting recommendations. In order to address such concerns, I conduct a series of robustness tests to rule out various alternative explanations for the effects I document. During the same post period, there have been two major events in the US mortgage market. Starting from 2017, there has been a gradual increase in the conforming loan limits for mortgages to be eligible for purchase by the GSEs whereas the FHFA introduced the language access plan in 2018 for borrowers who have low English proficiency. Across various specifications, I show that the results are robust to the increasing conforming loan limits as well as the reduced language frictions stemming from the language access plan. Next, I show that high DU dependent counties did not experience improvements in mortgage lenders' deposits as well as shadow bank credit lines which helps alleviate concerns that differences in funding conditions explain the results. I also rule out concerns that the increase in approvals is due to an improvement in the profile of the pool of borrowers applying for a mortgage in treated areas. Lastly, I conduct two additional robustness tests. I utilize an alternate data which is the set of single family mortgages purchased by the government sponsored enterprises (GSEs), Fannie Mae and Freddie Mac. Using the GSE purchase data, I show that share of mortgages in the affected, high debt-to-income group among the GSE purchased mortgages precisely increase only after the DU software update. Second, I verify that the results are consistent to baseline results in alternate lender level specification.

After supporting the internal validity of the baseline results, I explore the implications for credit risk due to the increased mortgage approval rates. Following the logic of standard credit rationing models, lower denials can lead to higher average credit risk if riskier borrowers enter the market. However, I do not find evidence consistent with such explanations. In loan level analyses, I find that the 2 year delinquency of loans in the affected, higher debt-to-income group is not statistically different from that of the loans in the unaffected, lower debt-to-income group after the policy change. Complementing the loan level analysis, I find that more exposed counties also did not experience higher delinquency rates after the positive shock in DU recommendations. I also show that there is no effect on delinquency even when borrowers are exposed to stressful economic scenarios and likely to default more. That is I do not find evidence of increased delinquencies even in the sample of the borrowers experiencing the highest growth in unemployment rates. This suggests that increased credit access may not have been accompanied with a deterioration in borrower quality but rather that some creditworthy borrowers were previously denied access to credit.

I then study the drivers of the increased approvals for mortgage credit applications stemming from the shock to DU recommendations. It is important to note that the DU underwriting policy change not only affects lending standards but is also concurrently a positive shock to securitizeability of loans and hence results in a relaxation in securitization standards. That is, given that DU is provided by Fannie Mae, a government sponsored enterprise (GSE), an approve recommendation from DU is a signal about the eligibility of purchase by the GSEs. Therefore, lenders who have greater incentives to securitize their originated mortgages are more likely to be influenced by the DU recommendation shock since they can sell originated mortgages to the GSEs. Unlike traditional lenders, non bank lenders do not have access to stable deposit financing (E. Jiang et al., 2020), so they rely on short-term warehouse credit lines which are collateralized by the originated mortgages and repaid once the mortgage is securitized (Gete & Reher, 2021; Kim et al., 2018) which suggests that non banks should respond more. Consistent with this, I find that the increase in mortgage approvals from the DU recommendation shock is more pronounced in counties with greater market share of non bank lenders prior to the shock.

An approve recommendation is also an information about borrower quality. If we assume that there is no other information on the borrower through perhaps additional or alternate ways of screening, this recommendation will serve as the most salient signal of borrower quality for the lender in determining whether or not to extend credit. However, given individual mortgage loan officers still interact with borrowers and work with applicants to collect more, especially soft information (Agarwal et al., 2011)[4]. Therefore, this human involvement from the lenders' side during the application process means that they can augment the information from automated underwriting system and thus play a role in the final loan decision or even assist in manually underwriting loans which fail to get approved by automated underwriting system. This suggests that the increase in mortgage approvals resulting from the DU shock should be lower where there is a greater scope of human interaction between the borrower and lender. First, as a proxy for loan officer involvement in the lending process, I classify counties according to the number of registered loan officers per applicant. I find that the increase in approvals are lower where there are more loan officers per applicant. Second, as a more direct measure for borrower-lender interaction, I classify counties based on the market share of lenders in a county where the completion of the entire application process does not require any human intervention. I find that the effect of the DU shock is more pronounced in such counties.

I assess the aggregate impact of the shock to DU recommendations and its contribution to approval rates. In an aggregation exercise under the assumptions of partial equilibrium and well defined control groups, I find the update to DU accounts for 26% of the increase in mortgage approval rates. Next, I explore which borrowers benefit more from the DU shock. I study the differences in mortgage approvals across racial groups. I find that evidence after the DU update, there has been comparatively more benefits to racial minority borrowers more compared to white borrowers as mortgage approval rates increase more in areas with non white borrowers. I then study whether increased mortgage origination from the DU shock benefits previously underserved areas. In the context of the US mortgage market, if borrowers are denied credit due to negative DU recommendations, they can opt for Federal Housing Administration (FHA) loans instead of the standard conventional loans. However, frictions to such substitution implies existing borrowing constraints which can result in amplified effects (Bemanke & Gertler, 1989). After the

[4]Regulatory reforms after the financial crises has contributed to a more labor intensive process of mortgage lending (D'Acunto & Rossi, 2022).

financial crisis, the Department of Justice sued many lenders under the False Claims Act for their FHA lending activity which has resulted in many lenders subsequently reducing their participation in the FHA loan market leaving a potential void in the availability of FHA loans. Using the pre-litigation mortgage market share of FHA lending by affected lenders, I find that conventional mortgage origination is higher in those DU reliant counties where there is a greater activity in the FHA loan market from litigated lenders.

Lastly, I study the real effects of this policy change both in the housing market and beyond. First, I find that the rate of owner occupied homes increases in the most exposed counties suggesting that those marginal borrowers, who are in need of mortgage credit the most benefited from the change. Consequently, this lowered the rent growth in more exposed counties consistent with a potential decrease in demand for rentals (Gete & Reher, 2016, 2018; Gete & Zecchetto, 2018) as owner occupied homes increase. Moving from the 25th percentile to the 75th percentile of exposure to DU usage, this represents a 0.4 percentage point increase in home ownership rate and a 1 percentage point decrease in annual rent growth. Second, as many lenders are also active in other markets in addition to the mortgage market, I see whether increased mortgage market participation by exposed lenders crowds out commercial credit. Comparing high DU usage banks to low DU usage banks lending to the same county in the same year, I find that more exposed banks reduce their small business lending, especially on the intensive margin.

This paper contributes to several strands of literature. It is most related to the growing literature of the role of technology in mortgage markets (Bartlett et al., 2022; Berg et al., 2022; Buchak et al., 2018; Di Maggio & Yao, 2021; Erel & Liebersohn, 2022; Fuster et al., 2019; Johnson, 2023) and consumer credit in general (Chu et al., 2023; Costello et al., 2020; D'Acunto et al., 2022; D'Acunto & Rossi, 2023; Jansen et al., 2023). Some studies explicitly focus on the effects of algorithms in mortgage market (Bhutta et al., 2022; Blattner & Nelson, 2021; Das et al., 2023; Fuster et al., 2022; Gao et al., 2023; E. X. Jiang et al., 2021) and study the implications for inequity across minority groups and racial disparities in credit access. In contrast to these studies, this paper uses a policy change to study how different lending models respond to algorithmic recommendations and how it causally affects credit allocation. Moreover, different from recent evidence of hardening of soft information through financial technology (Berg et al., 2020; Liberti & Petersen, 2019) , the results in this paper suggests that soft information may still be relevant, at least for mortgage lending as the effects of automated recommendations on the final outcome of applicants is lower where borrowers are more able to have human interaction with lenders.

This paper is related to the burgeoning literature focusing on the growth of technological infrastructure in lending services. Studies have focused on broadband and internet facilities (Ciciretti et al., 2009; D'Andrea et al., 2021; E. X. Jiang et al., 2022), communication by telegraph (Lin, Ma, Sun, & Xu, 2021), mobile and digital banking (Dante & Makridis, 2021; Haendler, 2022; Koont et al., 2023). In the mortgage market, some papers focus on measuring banks' adoption or investment in technology through Information technology (IT) expenditure (S. Jiang et al., 2023) or through patents or IT specific employment (Shen et al., 2023). This paper builds on these papers by providing a more direct measure of the exact technological system used in evaluating mortgage loan applicants instead of measuring technology adoption and it also does this for all mortgage lenders and is not confined to simply banks. It achieves this by collecting new regulatory data on the usage of a major underwriting system.

Lastly, this paper contributes to literature on policies affecting different aspects of household leverage (Acharya et al., 2022; DeFusco et al., 2020; Johnson, 2020; Kinghan et al., 2022; Kuttner & Shim, 2016; Laufer & Tzur-Ilan, 2021; Van Bekkum et al., 2019). Most of these studies focus on the direct effects and efficacy of macroprudential regulations by governments introduced after the financial crisis on curbing lending and house prices. As opposed to directly restricting household leverage, this paper studies the effects of relaxing evaluation criteria while underwriting loan applicants in a particular leverage bracket on lenders' decisions.

The paper is organized as follows. Section 2 describes the institutional details and the changes in Desktop Underwriter. Section 3 describes the data. section 4 describes the research design. Section 5 presents the empirical results of this paper while section 6 concludes the paper.

2 Institutional Background

2.1 Mortgage Underwriting

The mortgage application process consists of four broad steps which include the application, processing, underwriting and closing. In the beginning, the process consists of prospective borrowers contacting lenders or brokers (who may work with multiple lenders) about their interest in getting a mortgage and formally submitting an application for a mortgage. Loan officers make sure all documents are properly submitted along with the application. Sometimes there are loan processors involved in this stage who may be different from loan officers and work together with loan officers in application processing. After the prospective borrower passes these initial stages, comes the mortgage underwriting procedure which is very streamlined (Ross, Turner, Godfrey, & Smith, 2008). It is a process through which credit seeking borrowers are screened by lenders which comprises of obtaining and verifying important documents and financial information as well as conducting background checks of loan applicants in order to assess the loan applicant's credit risk.

Over the years, the advancement of technology along with the availability of extensive data on consumer profiles has enabled technology to play an increasingly important role in mortgage application screening and evaluation. Crucial to this study is that although underwriting was done manually in the past century, automated underwriting has been the standard practise in the modern era. This was facilitated with the shift to automated underwriting systems (AUS) for algorithmic mortgage underwriting at the start of this century (Straka, 2000; Wells, 2023). These systems provide recommendations to lenders about loan applications based on statistical analysis and risk assessment of borrowers' information.

The information contained in the application is entered into an automated underwriting system. The system scores the application on credit risk based on the information provided. It is done through statistical analyses of default models and then provides a recommendation about the loan application. In the context of this study, I focus on Fannie Mae's Desktop Underwriting system (DU) which is the largest underwriting system and is a government automated underwriting system. It is used for underwriting conventional loans, which form the largest category of loans available to borrowers seeking to apply for a mortgage in the US. An approve recommendation from this system indicates that the loan is deemed within acceptable risk standards and is also eligible for Fannie Mae's program (Bartlett et al., 2022)[5]. Loan applications which are rejected

[5]While Fannie Mae loans are generally run through DU, A decent share of Freddie Mac loans are also run through DU. As such loans which have been approved and deemed as eligible for Fannie Mae have also been purchased by Freddie Mac. This is because DU rose to prominence as the major automated underwriting system overshadowing Loan Prospector (LP), another AUS for underwriting conventional loans provided by Freddie Mac. There was no strict requirements for the program specific use of AUS. Moreover, both Fannie Mae and Freddie Mac AUS are free to use by lenders. See https://www.housingwire.com/articles/34276-fannie-mae-eliminates-desktop-underwriter-fee/.

by the system receive a ’refer with caution’ recommendation.

Nonetheless, as Bhutta et al. (2022) points out the usage of such underwriting systems is widespread across various lending models and purposes. They note that lenders still utilize such underwriting systems to assist in underwriting even for those loans they have no intention to sell through a government program. According to them, close to 80% of loan applications among loans held on the portfolio of the originating lender were run through an automated underwriting system. In addition, they also find that lenders also portfolio loans which are eligible for securitization by the GSEs and about 90% of such portfolio loans received positive recommendation from automated underwriting system. Consistent with their findings, figure A.1 shows that the number of mortgages approved by DU is much larger than purchases made by Fannie Mae [6]. In addition, figure A.2 shows that the usage of DU measured by the fraction of total loans evaluated through DU is similar across various types of lenders even though they may have differing incentives and propensities of mortgage loan securitization (Kim et al., 2018).

Even after an approve recommendation from the system, the final outcome is decided by the underwriter. Although a recommendation is made by the system conditional on the information entered, the documents of loan applicants are separately and closely examined. In some cases, the loan may be denied by the lender if there is failure in verifying applicant information or if the property appraisal is lower than expected. In other cases, there could be need of additional explanation from borrowers if they have any issues in their credit profile. In this case, loan officers may help the applicant provide an adequate response due to a blemish in, for example their credit report or other supporting information. Lastly, manual underwriting can still be carried out if borrower cannot pass the automated underwriting system.

2.2 Desktop Underwriter Policy Change

The Desktop underwriter (DU) model assesses a borrower’s willingness and ability to repay their monthly mortgage obligation. This model is estimated using millions of mortgages originated over the course of several years and through a variety of economic environments [7]. The Federal

[6] Fannie Mae also purchases some mortgages which are never run through DU. However the data cannot distinguish this set of mortgages.

[7] Fannie Mae does not disclose the algorithm for DU. However it considers several risk factors such as the debt-to-income, credit score, loan terms, loan to value ratio, liquid reserves, occupancy type and variable income among many

Housing Finance Agency, which regulates Fannie Mae, sent out a directive in April 2017 to both government sponsored enterprises to eliminate any additional factors imposed to the standard evaluation model for any loans with the maximum allowable debt to income ratio of 50% [8].

Up until July 2017, DU had imposed additional factors on top of the standard model based risk assessment for loan applications submitted to DU with debt to income ratio between 45% to 50%. However, Fannie Mae made significant changes to its Desktop Underwriting system during its software update in July 29, 2017 to be in line with the FHFA directive. The DU model had an update it its risk assessment and it also removed the additional factors it considered for loans with debt to income ratio between 45 and 50. This was made possible was due to a more accurate assessment of loans in the high debt to income range without the need for additional requirements. Among the factors enabling this change was an improvement in the quality of the data used in the DU model. Prior to the financial crisis, many loan characteristics provided by lenders had deteriorated (Piskorski et al., 2015), which also included income and various components of debt. These include borrower incomes being misreported, incorrectly calculated or not supported with proper documentation (Ambrose et al., 2016; W. Jiang et al., 2014; Mian & Sufi, 2017) as well as under reporting of mortgage liabilities such as second liens (Griffin & Maturana, 2016b). This made it difficult to accurately capture debt to income ratio. However, recent years saw a decline in such defects in the loans originated. This was brought about by significant improvement in lender origination practises, processes and controls and the adoption of various tools and data verification practises. Given such improvements in the overall underwriting process, it has led to an increase in the reliability and accuracy of the loan level data used by the DU model and its ability to better and effectively model credit risk.

In order to see how these updates to the DU software in July 2017 impacted the recommendations of loan applications, I utilize Fannie Mae's internal data on all loans submitted to their DU system and observe their recommendation patterns over time. I plot the rejection rates for loan applications every quarter from 2016 to 2019. I use the term rejection to refer to loans which are not approved by DU. In figure 1, we see that prior to third quarter of 2017, for applications above debt to income ratio between 45 and 50, the reject recommendation rate was about 50%,

other factors. https://selling-guide.fanniemae.com/Selling-Guide/Origination-thru-Closing/

[8]See https://www.fhfaoig.gov/sites/default/files/WPR-2019-002.pdf

whereas it is only about 10% for loans with debt to income ratio less than 45. However, starting from the third quarter of 2017, the rate of reject recommendation for loans with debt to income between 45 and 50 drop by about 40% and it becomes similar to that of loans in the lower debt-to-income group. Figure A.3 breaks down the reject recommendation rates for loans in the lower debt to income group into three further groups of: (a) less than 40, (b) between 40 and 43 and (c) between 43 and 45 and finds similar trends across these three groups. We see that the drop in reject recommendation is specifically for applications with debt to income ratio between 45 and 50.

[Insert Figure 1]

3 Data

Mortgage Data Data on all mortgage applications is collected from the Home Mortgage Disclosure Act (HMDA) data. HMDA reports information on the near universe of all US mortgage applications. Relevant to this study, the dataset provides information including the lender name, year of application, application outcome, loan type, lien status, location of the property as well as information on borrower income, race and ethnicity. I keep all first lien, completed conventional mortgage applications[9]. The key outcome variable is the mortgage approval rate which is measured as the number of successful applications (loans originated or loans approved by the lender but not accepted by the borrower) divided by the number of complete mortgage applications. I restrict my sample to counties with at least 25 mortgage applications each year.

Desktop Underwriter My study crucially depends on data on the automated underwriting system used by mortgage lenders. However, it is not readily available in any mortgage market related data sources for the time period of this study. I collect confidential data on the usage of desktop underwriting system (DU) provided by Fannie Mae. These data are obtained through a Non Disclosure agreement with Fannie Mae. I was provided with counts of the number applications submitted and processed through DU by lender name and location of applications based on county in a given year. As there is no formal identifier for the lenders reported in the Fannie Mae data, I

[9] This includes all applications which are either originated, approved by the lender but not accepted by the borrower or denied

merge lenders in the Fannie Mae data to the HMDA data based on lender name and the county from which lenders receive applications in both data sets. Fannie Mae also provided information on how loans were approved in DU based on broad debt-to-income ranges at the quarterly level. The measure of treatment intensity for this study is described in detail in the following section.

Funding Data Since shadow banks play an important role in the the mortgage market, I obtain shadow bank funding information from mortgage call reports (MCR). I obtain this data from the Washington State Department of Financial Institutions through a public records request. Pursuant to the S.A.F.E. Mortgage Licensing Act of 2008, shadow banks which hold a state license or registration are required to file call reports with their state regulators. This data contains key information on shadow bank funding sources such as their warehouse of lines of credit and the associated credit limit in each of these credit lines. I also collect traditional bank deposit funding information from the FDIC Summary of Deposits data.

Loan level Data I obtain information on loan level information from the GSE single family databases provided by Fannie Mae and Freddie Mac. These data contain information on the month of loan origination along with other loan level characteristics not reported in the HMDA data. This data also reports information on loan performance.

Bank Balance Sheet I obtain quarterly information on bank balance sheets from the Consolidated Report of Condition and Income (Call Reports) provided by Wharton Research and Data Services. This information include total assets, deposits, equity, net income, net interest margin and cash. For a given year, I match each bank to the balance sheet information from the last quarter of the previous year.

Other Data Information on small business lending activity by each bank in a county comes from the Community Reinvestment Act data. County level information on subprime population come from Equifax data from FRED, Federal Reserve Bank of St. Louis. County level home ownership data comes from the American Community Survey whereas data on county level rent growth comes from Zillow. County level information on various economic and demographic characteristics come from Bureau of Labor Statistics, Bureau of Economic Analysis and the American

Community Survey.

4 Empirical Research Design

4.1 Main Specification

I exploit the regional variation in usage of the Desktop Underwriting system to study the impact of the DU software update. This allows me to study not only regional differences in credit access but also the real effects of the DU recommendation shock. In my baseline specification, I study the effect of DU reliance on the county level overall mortgage approval rate after the 2017 change in DU software over the period of 2014 to 2019. A county level analysis allows for inspecting the net impact on credit access at stable geographic units from the update to DU [10]. Moreover, I specifically focus on mortgage approvals because it indicates whether or not in a given applicant pool, additional applicants eventually end up being offered mortgage credit by lenders. As such, my initial goal is to measure the effect of DU recommendations on the extensive margin of credit access. I rely on a continuous treatment intensity based exposure variable at the county level based on pre policy data. Prior studies have used continuous treatment variables for policy exposure (e.g. Acemoglu et al., 2004). I estimate difference in difference models of the following form:

$$Y_{c,t} = \alpha + \beta(DUshare_c \times Post_t) + \gamma' \mathbf{X_{c,t}} + \eta_c + \psi_{s,t} + u_{c,t} \tag{1}$$

where c indexes counties, t indexes years. $Post_t$ takes the value of 1 for years where there is an updated DU system, that is from year 2017 and onward [11]. $\mathbf{X_{ct}}$ represents time varying controls at the county - year level. η_c & ψ_{st} represent county and state - year fixed effects respectively. I cluster standard errors by county when estimating equation 1.

In terms of interpretation of equation 1, the measure of treatment is $DUshare_c$ which captures the dependence of counties on DU underwriting system prior to the software update. It is measured as follows:

[10] This approach can account for the possibility of a reallocation of the affected group of applicants between unaffected and affected lenders and allows for studying the implications on overall credit access.

[11] The main analysis is based on the HMDA data which is reported at the yearly level. So $Post_t$ is equals 1 from the year of treatment. In later tests, I redefine this variable where there is more flexibility on the time dimension.

$$DUShare_c = \frac{\textit{Loans submitted to } DU_c}{\textit{Total loans}_c}$$

where $DUshare_c$ is the fraction of all loan applications submitted through DU in a county in 2016 [12]. I only consider first lien loan applications while calculating $DUshare_c$ since only first lien loans are eligible to be run through DU underwriting system. Figure 2 shows the geographic variation of $DUshare_c$ across counties in the US.

[Insert Figure 2]

4.2 Identification Assumption

The parameter β in equation 1 recovers the effect of the shock to DU recommendations from the software update on mortgage approval rate only if the following identification assumption holds:

$$\mathbb{E}[DUshare_c \times Post_t \times u_{c,t} | \mathbf{X_{c,t}}, \eta_c, \psi_{s,t}] = 0 \tag{2}$$

In words, the assumption in 2 states that counties where lenders have relied on underwriting mortgage loans through DU are not predisposed to non-DU shocks to mortgage approval rates that coincide with the update of DU. I take a few steps to substantiate this assumption. I include county fixed effect η_c that absorbs time invariant and slow-moving, county-specific factors that may affect the outcome of interest, while the inclusion of state - year fixed effects $\psi_{s,t}$ absorbs state specific aggregate factors affecting all counties within the same state at the same time. Despite this there may be concerns that county level exposure to DU underwriting may not be randomly assigned. The counties with high exposure to DU may be different from those counties with a low exposure to DU along a number of dimensions. I compare counties with above and below median exposure to DU on various economic and mortgage market related characteristics in Table 2. I find that while the counties are similar in terms of dependency ratio and the mortgage market share of traditional bank lenders, the counties do differ along the lines of household income, unemployment rate, the fraction of population with credit scores below 660 and proportion of non-white mortgage applicants. To address these differences I control for these variables in my regression.

[12] Since I match underwriting activity in DU to HMDA based on lender name and the county of its lending activity, precisely, the measure $DUshare_c = \frac{\Sigma_l \omega_c \times loan_{l,c}}{\Sigma_l loan_{l,c}}$ where ω_c is the DU usage share for lender-county pair l, c in HMDA.

[Insert Table 2]

Despite these steps, there could be concerns that there are other changes to areas more exposed to DU which is not accounted for. For instance, if there are a lot mortgage applicants of lower quality or lenders with worse financial conditions in the more exposed areas, then mortgage approval rates could already be lower before the change in DU software. I explicitly test for such possibilities in formal tests in the sections following my baseline results. At this stage, for a more direct evidence assessing the validity of this assumption, figure 3 plots the annual coefficient estimates of the dynamic version of the equation 1. My core assumption here will be violated if the outcome of interest would have evolved differently across locations with varying exposures to DU in the absence of the DU software update policy. The estimates from this event study in figure 3 shows that mortgage approval rates for high and low DU reliant counties exhibit parallel pre trends leading up to the DU software update but only diverge afterwards. This finding helps support the validity of assumption 2.

[Insert Figure 3]

5 Empirical Results

5.1 Impact on Mortgage Credit Access

5.1.1 Baseline Results

I first examine how the shock to DU underwriting standards affects the extensive margin of credit access. Here I compare credit access between counties with greater and lower dependence on Desktop Underwriter (DU) before and after the software update in 2017. My primary measure of credit access is the mortgage approval rate at the county level. Under the null hypothesis, we should expect no impact on approval rates resulting from the DU policy change. Employees at lending institutions could utilize alternate underwriting methods for these unsuccessful applications. Especially under no capacity or time constraints, they may put effort in working through each unsuccessful application and may even modify and adjust applications to loan terms at which the respective lenders find optimal to extend credit based on their assessment of applicant. They may even submit all initially unsuccessful applications multiple times to the underwriting system during the whole application process and eventually set loan characteristics within those thresholds which satisfies the approval criterion of the underwriting system[13]. In such a scenario, we could expect that the eventual approval rates between borrowers who pass and do not pass the criterion set by the underwriting system will not be much different from each other. The alternate hypothesis is that there are frictions to having an equally effective alternative way to accommodate and evaluate those borrowers who may not be favourably assessed by the automated underwriting system. Under the alternate hypothesis, there should be a direct impact on actual approval rates from the DU policy change. My baseline estimations test between these competing hypotheses.

Table 3 presents the results from the difference in difference estimates of equation 1 with approval rate as the dependent variable. Approval rate is the number of lender approved applications out of total completed mortgage applications in a county. Approved loans include loans which were originated as well as those loan applications which were approved by the lender but not accepted by the borrower. All columns include county fixed effects. Column (2) additionally controls for county level characteristics which include the median household income, unemployment rate, fraction of subprime population and the fraction of non white mortgage applicants in a county. In addition, Column (3) includes year fixed effects while column (4) includes state-year fixed effects to ensure that the comparison is between counties within the same state and year in order to absorb time varying state level factors. The estimates suggest that greater reliance on desktop underwriter in a county leads to increased mortgage approval rates after the DU update. Across columns (1) to (4), the estimates range from 5-6.8 percentage point and all coefficients are statistically significant at the 1% level. Moving 25th percentile to the 75th percentile in the county level distribution of the share of loan applications processed through DU, the most conservative estimates suggest that mortgage approval rates increased by about 1 percentage point. The magnitude of this effect is sizeable. Given the pre-period unconditional mean in approval rate among applications which were complete and received a decision was 72.6 percentage point, this represents an increase of about 1.40% in approval rates for the average county before the DU update.

[13] In the case of the DU underwriting policy change, this would be the borrower's debt to income ratio being adjusted to no more than 45 in the loan application from an initial level of over 45.

Moreover, since a 100% increase in DU share is estimated to increase mortgage approval rates by 5%, multiplying 5% with the pre-period market share of DU usage, I estimate that mortgage approval rates increased by 2.3 percentage points[14].

[Insert Table 3]

There are challenges to identification in estimating the effect of DU update on mortgage approval rates. One obvious concern is that the independent variable, *DU share* is correlated with certain observed and unobserved county-level measures which may reflect sharp heterogeneous changes in economic activity around the same time period as the update to Desktop Underwriter. In table 2, we can see that counties more exposed to DU have higher median incomes, lower unemployment rates and lower subprime and minority shares. For instance, if there are concurrent events which result in disparate economic activity in the mortgage market along these observed dimensions which are also correlated with DU usage, then it will be difficult to disentangle these effects from the effect of the DU update. In appendix Table A.1, I show that the effects on mortgage approvals resulting from the DU update is robust to explanations such as county level DU usage capturing the effects of any potential differential mortgage market activity along these observed county level characteristics around the same time period as the DU update. Furthermore, in section 5.2, I show that this baseline result documented in Table 3 is robust to various other alternative explanations.

5.1.2 Additional Evidence

The baseline results in Table 3 strongly indicate that the update to the DU software resulted in an increase in mortgage approvals. This suggests that additional borrowers had availability of mortgage credit than before. Next, I provide further evidence that this increase was indeed due to the changes to DU affecting the group of borrowers in the particular segment of debt to income.

The update to the Desktop Underwriter affected recommendation outcomes particularly for borrowers with a debt to income ratio between 45 and 50. Therefore, if the increase in approval rates I document is due to the Desktop Underwriter update, then approvals should increase more in areas where there is both a greater reliance on Desktop Underwriter and a greater presence of

[14] The share of loans underwritten through DU in 2016 was 46%. Hence, the estimated effect is 46% $\times$ 5% = 2.3%.

applicants with such debt to income ratio. In order to test this, I first create a variable at the county level, *Affected App share* measuring the share of loan applications in DU with debt to income ratio in affected range in the year before treatment. I then create the variable of interest capturing the potential share of total applications in county likely to be affected based on pre-treatment year data, *DU share* $\times$ *Affected App share*. I then estimate the following model with approval rate as the dependent variable:

$$Y_{c,t} = \alpha + \beta(DUshare_c \times Affected\ App\ share_c \times Post_t) + \gamma'\mathbf{X_{c,t}} + \eta_c + \psi_{s,t} + u_{c,t} \tag{3}$$

Table 4 presents the results from estimates of equation 3. Across all columns, the estimates range from 41.4%-45.2%. This estimate suggests that for any given county entirely dependent on DU for automated underwriting as well as having borrowers only the affected debt to income segment, the mortgage approval rates would increase by about 40%. This finding supports that the increase in mortgage approvals was indeed due to applicants who benefited from the update to DU. Figure A.6 also confirms the existence of parallel trends in approval rate before the DU update.

[Insert Table 4]

The update to the Desktop Underwriter positively affected recommendation outcomes particularly for borrowers with a debt to income ratio between 45 and 50. In figure 1, we see that the approve recommendations for these borrowers increased by about 45% in the post period compared to the pre policy period. Approximately 7.6% of all mortgage applications were in this affected debt to income range in the one year immediately preceding the policy change based on applications submitted to DU. Assuming a one-to-one increase in mortgage approval based on DU recommendations and no change in borrower composition as well as ignoring any substitution, this would suggest an increase in mortgage approvals of $(.076 \times 0.45 \times 100 =)$ 3.42 percentage points. However, if we simply consider applications with debt to income over 45 in the pre policy period, about 11.3% of all applications, this would suggest an increase of in mortgage approvals of 5.08 percentage points, which is very similar to the baseline results obtained in Table 3. This suggests that some borrowers who were above the debt to income of 50 and hence would not have received approve recommendations from DU earlier may have bunched to debt to income levels below 50 after the DU policy change in order to facilitate credit access for such borrowers[15].

5.2 Robustness

5.2.1 Confounding Regulatory Events

While my baseline results suggest an increase in approval rates from the shock to DU recommendations, there may be concerns that it could be biased due to confounding events affecting the mortgage market simultaneously with the update to DU.

First, starting from 2017, the federal conforming loan limits has been increasing every year. Loans which fall under this limit are more liquid since they satisfy the eligibility criteria for GSE backing (Loutskina & Strahan, 2009). Thus these loans are more likely to accepted than loans which are over this threshold. If counties which are more exposed to the DU recommendation shock are also more exposed to the expanded set of loans satisfying the conforming loan limits, then my baseline results could be biased upwards. In order to assess this possibility, I re-estimate equation 1 after controlling for the share of loan applications within the conforming loan limits in a county each year, denoted by *Conforming Share*. In Columns (1) and (2) in Panel A of Table 5 shows that the coefficient of interest is similar to its analogue from Table 3. Moreover, in column (3) I calculate approval rate after excluding the set of additional loans each year which satisfy the conform loan limits while in column (4) I calculate approval rate only for loans below the conforming loan limit in 2016[16]. Again I obtain results which are similar to the estimates from the

[15]If comparatively better borrowers in the category of debt to income over 50 bunch at debt to income levels below 50 after the policy change, it would suggest that quality of borrowers in the pool of mortgage applicants with debt to income of over 50 deteriorates after the DU policy. In line with such an argument, figure A.5 shows that DU rejection rates for applications with debt to income over 50 increased after the update to DU. Moreover, there is indeed the possibility that borrowers who were bunching at the debt to income level of 45 prior to the DU update are now able to have higher debt to incomes after the policy change. This would not necessarily affect the DU evaluations since it is likely that such borrowers were already getting approved for credit prior to the update albeit at level of leverage lower than a debt to income ratio of 45. As such there seems no noticeable change in DU approve recommendations for applicants with debt to income lower than 45 after the DU update as shown in figure 1 and hence these increases in borrower leverage is not likely to contribute to eventual mortgage approval rates by lenders. In addition, there is also the possibility of emergence of borrowers who did not apply for a mortgage prior to the DU policy. Nonetheless, a formal bunching estimation exercise is beyond the scope of the paper due to limitations of not having detailed loan level data of on all mortgages with information on debt to income before and after the policy change.

[16]I consider loans below \$410,000 instead of \$417,000 since the HMDA data reports loan amounts in ranges of 10,000 starting from 2018.

baseline result.

[Insert Table 5]

Second, starting from 2018, the Federal Housing Finance Agency (FHFA) introduced the multi year Language Access Plan in order to ensure that mortgage ready borrowers with limited English proficiency are better able to understand and participate in all aspects of the mortgage process and identify and remove obstacles in their accessibility to mortgage credit[17]. Importantly, a clearinghouse with a centralized collection of resources to assist lenders, servicers, and housing counselors in serving such borrowers was launched. The clearinghouse website provided translated mortgage documents in Spanish from 2018 followed by Chinese translations from 2019. If borrowers who benefit from such policies are also from counties which are more reliant on DU for mortgage underwriting, then again the baseline results may be biased upwards. I create two variables at the county level, *Low English Population* and *Low English Household* which captures the share of people with limited English proficiency potentially affected by this policy each year[18]. Panel B of Table 5 shows that estimates on the coefficient of interest is similar from the estimates from the baseline results in Table 3.

Another policy similar to the DU update was implemented by the Federal Housing Administration for the underwriting of FHA loans in August 2016, which allowed for a transition from strictly mandated manual underwriting to the availability of algorithmic underwriting for borrowers with low credit scores i.e below 620 and debt to income ratios of over 43 [19]. Although the timing of this policy is similar to the update to DU, this is not a concern for the current analysis. This paper focuses exclusively on conventional loans, whereas the Federal Housing Administration underwriting policy was for FHA loans underwritten through their TOTAL scorecard system. Conventional loans comprise the lion share of the US mortgage market whereas FHA loans form a much smaller share of all mortgage loans. The 2016 FHA policy specifically impacted borrowers who would generally not qualify for conventional loans which require credit scores over 620.

[17]For further details, see: https://www.fhfa.gov/PolicyProgramsResearch/Policy/Pages/Language-Access.aspx

[18]Specifically, *Low English Population* equals 0 for years 2017 and before and it equals the share of limited English speaking Hispanic population for the year 2018 and it equals the sum of limited English speaking Hispanic and Chinese population for the year 2019. *Low English Household* is defined analogously for households.

[19]For further details, see: https://www.cfsreview.com/2019/03/hud-updates-fha-total-mortgage-scorecard/

However, if low credit score loan applicants with debt to income over 43 shifted from the conventional loan market to the FHA loan market, then the pool of conventional loan applicants at the affected debt to income levels would have potentially improved leading to better DU recommendation outcomes for such loans. Nonetheless, there is no change in DU recommendations for such loans around the timing of the 2016 FHA policy. There is also no change in the quantities of conventional loan applications submitted to DU around the FHA policy suggesting that this policy might not have any discernible impact on the market for conventional mortgage loans [20].

5.2.2 Shock to Funding Conditions

The underlying assumption for the identification strategy is that the increase in approval rates was due to the DU update. However, a possible alternative supply side interpretation for such results is that lenders might have experienced a positive shock to their funding conditions, which lead to them approving more mortgages. In order to see whether such explanations are valid, I explicitly test for changes in funding conditions in the more DU exposed after the shock to recommendations.

Traditional bank lenders depend on deposit financing. However, non traditional banks comprise a major part of the mortgage market and any analysis on funding conditions must also include shadow banks. In order to extend mortgage credit, shadow banks rely on warehouse lines of credit with each credit line having a credit limit associated with it (E. X. Jiang, 2023). In Table 6, I formally test whether lenders in counties more exposed to DU experienced better funding conditions after the shock to DU recommendations. I create three variables, *ln(deposit)*, *ln(Credit Lines)*, *ln(Credit limit)* at the county level. These are the natural logarithm of the market share weighted average deposits, lines of credit, and total credit limit for mortgage lenders in a county-year. The coefficients in columns (1) to (3) are all negative with the coefficients in columns (2) and (3) being statistically significant, suggesting a decrease in aggregate terms along these three dimensions. Consequently, columns (4) to (6) conducts the same analysis using dependent variables in per capita terms. While per capita average deposits and per capita averge credit lines decrease in DU exposed areas after the DU update, there is no statistically significant effect on per capita average credit limit. Overall, these results suggest that an increase in approval rate in the areas more

[20]From author's undocumented calculation on number of DU submissions by debt to income over time.

exposed to DU is unlikely to be driven by improvement in lenders' funding conditions.

[Insert Table 6]

5.2.3 Change in Loan Applicant Profile

Another alternative explanation for the results I document is that DU exposed areas experienced an improvement in the profile of borrowers applying for a mortgage concurrently to the update to DU. Thus, it would be improved quality of the applicant pool driving the increase in approval rates in the DU exposed areas. Given that, on average, areas more reliant on DU started experiencing more positive recommendations while underwriting borrowers, there could be concerns that over time, lenders may have reacted to relaxed underwriting standards by ensuring that borrowers who may ex-ante seem more worthy of credit are the ones who can formally apply for mortgage credit.

In order to address concerns that an improvement in the applicant pool drives the result, In table 7, I estimate equation 1 using dependent variables which reflect observed characteristics of the pool of mortgage applicants. In columns (1) and (2), I find that counties more exposed to the DU did not experience a decrease in applications from minority applicants who are black or non white Hispanic after the DU update. Moreover, in columns (3) and (4), the findings suggest that applicants with income below the county median or county per capita income actually increased in the more DU exposed counties after the change in DU. This helps alleviate concerns the positive shift in the quality of borrowers explain the increase in approval rate.

[Insert Table 7]

5.2.4 Alternate Data and Specifications

In order to further support the credibility of my baseline results, I do two additional robustness tests. First, I also show that this change to DU was not anticipated by mortgage market participants. If this is to hold true, then the increase in loans within the affected debt to income range should only happen after the update to DU. To show this, I rely on monthly data on all originated loans in the GSE single family database by Fannie Mae and Freddie Mac. I estimate a dynamic version of 1 at the monthly level with the share of loans with debt to income between 45 and 50 as the dependent variable[21]. Figure 4 plots the monthly coefficient estimates and shows that the share of loans in the affected debt to income category increase more in the high DU reliant areas compared to low DU reliant areas only after the update to DU in 2017 July. In order to lend additional support to the result that the emergence of loans with debt to income over 45 is precisely due to the DU update in July 2017, I plot the monthly coefficient estimates similar to the specification in Figure 4 separately for purchases by Fannie Mae and Freddie Mac in Figure A.7. Given that almost all Fannie Mae purchases are run through the Desktop Underwriter, while only some of Freddie Mac purchases are initially run through the Desktop Underwriter (A large share of Fannie Mae loans are run through its own AUS, Loan Prospector), it should be that there are greater increases in the share of loans in the affected debt to income category resulting from the DU update for Fannie Mae purchases than for Freddie Mac purchases. Consistent with this, the monthly coefficients plotted in Figure A.7 are larger for Fannie Mar purchases than for Freddie Mac purchases after the DU update. Moreover, Table A.2 presents results of the difference in difference estimates on both monthly and yearly level regressions and reports a overall positive effect on the share of affected debt to income loan purchases in the treated areas.

[Insert Figure 4]

Second, I show that the results are also robust to lender level analysis. My baseline results rely on a county level difference in difference estimation where treatment is defined as the share of loans underwritten by mortgage lenders through DU. If there is an increase in credit access in counties more exposed to DU, this should also be reflected at lenders using DU. Now, I conduct lender-year level regressions to validate this[22]. The dependent variable is the mortgage approval rate for the lender in a given year. Table A.3 presents the results and shows that treated lenders, i.e. DU users increase their mortgage approval rates after the DU update. Thus, the findings are consistent with the baseline results.

[21]Given the data do not include information on the county from where the loan originated, I measure the treatment intensity variable, *DU Share* at the 3 digit zip code level.

[22]The regression specification is of the following form:

$$Y_{l,t} = \alpha + \beta(DU_l \times Post_t) + \gamma' \mathbf{X_{l,t}} + \eta_l + \psi_t + u_{l,t} \tag{4}$$

where DU_l is equals one if a lender used DU in 2016 or is 0 otherwise.

5.3 Impact on Mortgage Credit Risk

I now examine whether this expansion of credit has any implication for credit risk. If borrowers who are indeed not worthy of credit enter the market after the relaxation in DU recommendations, then the average borrower quality should decrease and the average credit risk should increase. I take two approaches to study the effect on credit risk. First, I estimate loan level regressions of the following form based on the set of purchases made by Fannie Mae:

$$Y_{i,t} = \alpha + \beta(DTI > 45_{i,t} \times Post_t) + \gamma' \mathbf{X_{i,t}} + \eta_{LTV \times FICO} + \psi_{z,t} + u_{i,t} \tag{5}$$

where following Fuster et al. (2019), the outcome variable is whether the loan was ever 90 day delinquent in the two years following origination. $DTI > 45$ is an indicator which equals one if the loan is in the affected category, that is if the debt to income ratio of the applicant is over 45. I restrict the sample to loans with debt to income between 40 and 50 and which originated in a symmetric time period of 7 months before and after the DU update[23]. I control for the interest rate, unpaid principal balance, loan term, mortgage insurance, whether the loan has mortgage insurance, whether it is a first time home buyer, the purpose of the loan and the occupancy status of the loan. I compare loans originated from the same three digit zip code in the same month by including zip by month fixed effects. I also include fixed effects for LTV by FICO grids (Bartlett et al., 2022).

[Insert Table 8]

In Table 8 Panel A, the coefficient estimates across columns (1) to (4) are positive and are close to zero. However, none of the coefficient estimates are statistically significant at conventional levels. This suggests that loans in the affected debt to income range may not be riskier than before since the ex post performance of the new borrowers are not any worse than the previous group of borrowers[24]. Moreover, event study estimates from Figure 5 show no differential effect on delinquencies on loans with debt to income over 45 compared to the unaffected control group of

[23] This ensure a period of at least 2 years before the start of Covid 19 in March 2020

[24] I also look into the interest rates charged on the affected high debt to income borrowers after the DU update. Results reported in Table A.4 show a very modest increase in interest rates of about 0.014 to 0.02 percent. This is an economically insignificant increase compared to the average interest rate of 4.3 percent in the period before the DU update. The slightly high mortgage interest rates for the affected group may be due to lenders' reaction to counter the relaxed standards for high debt to income borrowers.

loans in the months leading up to the DU update providing evidence on the validity of the parallel trends assumption.

In all the specifications in Table 8 Panel A, point estimates range from 0.001 to 0.002. Despite point estimates being statistically insignificant, given a standard error of 0.001 across the specifications, it means the estimated delinquency rates are at most 0.0026 to 0.0036 in 95 percent of the observed cases. Even if the tests are not sufficiently powered to detect statistically significant effects, a delinquency rate of 0.26% to 0.36% is comparatively small in magnitude when compared to unconditional mean of the delinquency rate for conventional loans in the pre period which is equal to 1.3%. I also complement the loan level analysis by estimating a version of equation 1 at the monthly level where the dependent variable is the 90 day delinquency rate of the county in Panel B of Table 8. Once again, the point estimates are close to zero and statistically insignificant [25] . Overall, this indicates that there may be no noticeable evidence of an increase in credit risk due to the change in DU . Moreover, it also suggests that rather than a deterioration in borrower quality from increased credit access, it suggests that some credit worthy borrowers were previously denied access to credit. These results are in contrast to studies focusing on the pre-crisis period where regulations allowed lenders to expand credit supply at the expense of riskier loan origination (e.g. Lewis, 2023).

[Insert Figure 5]

One of the potential reasons for observing no changes in delinquencies may be due to the fact the sample period coincides with a period of stable or rather booming housing market and overall economic conditions. As such instead of reflecting borrower quality, as mentioned above, the results may indicate a lack of power in my empirical tests since default rates have been low during such this time period. Borrowers are more likely to default and hence actual borrower quality may be better revealed when they are exposed to adverse or stressful economic scenarios. If indeed there is a deterioration in borrower quality from the increased credit access, then comparatively

[25] The lack of statistical significance is not due to the affected set of loans being a small portion of all mortgages. Loans belonging to the debt to income range of over 45 form a considerable share, which is 7.6% of all mortgage loans based on loan application submitted to DU in the one year prior to the policy change. Moreover, Figure A.8 also plots coefficients on delinquency rates where the exposure variable is a composite treatment explicitly accounting for the potential share of affected debt to income loans similar to Table 4 and finds no noticeable change in delinquencies based on this alternate specification.

higher default rates should occur in areas in high unemployment growth rates, since negative financial shocks from job loss will make borrowers more prone to default. In Table 9, I re-estimate the loan level regressions in sub samples based on quartiles of unemployment growth rates. I find that even in areas with the highest unemployment growth rates, I do not observe an increase in default rates for the affected group of borrowers. The results are further confirmed in triple difference regressions and in county level analyses in columns (5) and (6) where the I include the variable, *High* Δ*UnempRate* as an additonal interaction term. This provides further support to the claim that there is no evidence that borrower quality had worsened after the DU policy change.

[Insert Table 9]

5.4 Mechanisms on Access to Credit

In this section, I formally test the mechanisms behind the link between recommendations from automated underwriting system and the eventual mortgage approval by lenders. There are two mutually non exclusive channels through which a recommendation can result in an approval which I explore in detail in this section. First is the prospect of securitization and second is the lack of borrower-lender interaction to augment or substitute for automated underwriting.

5.4.1 Securitization Incentives

It is important to note that any automated underwriting system simply provides a recommendation about the loan to the underwriter (Bhutta et al., 2022), and the final outcome on a loan application will depend on the discretion of the specific lender and how it interprets the recommendation. Crucial to this study, the DU underwriting policy change concurrently results in a positive shock to the securitize-ability of loans along with affecting lending standards. As an underwriting system provided by a major government sponsored entity (GSE), DU's approval of a loan also signals that the loan meets the eligibility criteria for purchase by GSE[26]. So, if a loan is eventually originated by a lender after passing DU, it can be sold to the GSEs (Bartlett et al., 2022).

[26]DU produces loan assessments and GSE eligibility tests simultaneously. Loans accepted to DU can be delivered to Fannie Mae. Due to this, the DU underwriting change affects both the standards for lending and securitization at the same time.

Non bank lenders operate on a model which result in them having greater incentives to securitize their originated mortgages. This is because they depend on short-term warehouse lines of credit. The originated mortgages serve as collateral for this warehouse debt which is repaid once the mortgage is securitized (Kim et al., 2018). This is in contrast to traditional bank lenders who have access to stable financing through deposits (E. Jiang et al., 2020). Therefore, it suggests that non banks' response to positive recommendations should be higher, leading them to approve more mortgages.

In Table 10, I test whether non banks respond more to the DU recommendation shock. Following Demyanyk and Loutskina (2016) and Huszár and Yu (2019), I classify non banks based on whether lenders are not under the oversight of any federal supervisor since all depository institutions are subject to a federal supervisor. I create a variable called *High Non Bank* which equals one if a county is in the top quartile of mortgage market share of non bank lenders in 2016 or zero otherwise. The estimates across columns (1) and (2) show the counties with greater non bank lenders approved more mortgages in response to the shock to DU recommendations.

[Insert Table 10]

5.4.2 Borrower - Lender Interaction

An approve recommendation from the automated underwriting system serves as a signal about the quality of the loan applicant. In the hypothetical case that there are no other avenues for screening borrowers, the recommendation from automated underwriting system is the most salient information about borrower quality which a lender can rely on. However, mortgage loan officers still play an important role in mortgage lending through interaction between them and potential borrowers. Loan officers can work with applicants to collect more, especially soft information (Agarwal et al., 2011; Cortés, 2012; Keys et al., 2010; Stroebel, 2016) [27]. This can either augment the information from automated underwriting in determining the final outcome of the loan application or help in manually underwriting a loan in case it does not pass the automated underwriting system. So, lenders' ultimate decision may depend less on automated underwriting recommendations. This suggests that the increase in mortgage approvals resulting from the DU shock should

[27] Examples include stability of borrower's future income and local housing market fundamentals. Soft information is particularly relevant when the borrower is self employed (Saengchote, 2013)

be lower where there is a greater scope of human interaction between the borrower and lender.

First, as a proxy for the both the availability and the extent to which loan officers are able to allocate time and effort towards individual borrowers, I use data on state level counts of registered loan officers and create a measure *Loan Officer - High* which equals one if a state is in the top quartile of the number of loan officers per applicant in the pre treatment period or zero otherwise [28]. Columns (1) and (2) of Table 11 show that approval rates increased less in response to the DU shock where there are loan officers per applicant. As an alternative but a more direct measure of the (lack of) involvement of loan officers in the lending process, I create a variable *No Human - High* which equals one if the county is in the top quartile of the market share of lenders where no human intervention is required in the application process and zero otherwise[29]. Columns (3) and (4) show that approval rate increases more in such counties after the DU recommendation shock. Overall, the results suggest that approval rates respond less to the DU recommendation shock where lenders can either augment the automated underwriting process through collecting additional borrower information or provide alternate means for underwrite applicants when they do not pass automated underwriting.

[Insert Table 11]

It is important to note that non bank lenders generally function with low numbers of mortgage loan officers. In prior analyses, I utilize non bank status of lenders as a proxy for mortgage securitization incentives while I utilize the lack of loan officers per applicant as a proxy of lack of borrower lender human interaction. If there is a sufficiently high correlation between the share of non bank lenders in an area and the number of loan officers per applicant in an area, there can be a potential limitation in both the preceding tests. That is it would be hard to disentangle between both these channels affecting access to mortgage credit from the DU policy. While this is an important caveat to be acknowledged, correlation between the two measures suggest that this is not a big concern in terms of the tests being carried out in this section[30].

[28] I rely on state level counts due to data limitations. Data comes from the NMLS website.

[29] In such lenders, the entire application process does not require borrowers to come in personal contact with lenders up until firm rate quote. Data comes from Buchak et al. (2018)

[30] The correlation between *High Non bank* and *Loan officer - High* is only -0.156. This suggests that the two tests are valid in the sense that at least econometrically they are capturing two sufficiently distinct concepts. Moreover, the lack of granular data on the lender level number of loan officers by location preclude me from exploring the human

5.5 Aggregate Implications for Mortgage Approvals

I perform an aggregation exercise using point estimates from Table 3 to calculate the counterfactual growth in mortgage approval rates under the absence of the update to DU. Specifically, I ask how much lower will the increase in approval rates be under this counterfactual. In other words, what is the share of observed increase in mortgage approval rates attributable to the change in DU underwriting, denoted by η. I perform the following exercise to calculate this statistic. This requires two additional assumptions, both of which reflect that I obtain identification from the cross-section.

Assumption 1 (Control Group) The effect of the DU update on mortgage approval rate is zero in counties whose value of $DU\ Share_c$ is below B^{th} percentile of $DU\ Share_c$ across counties. These counties are defined as the control group.

Assumption 1 is required since I have a continuous measure of treatment exposure and I need to define a minimum threshold for this measure below which a county is effectively unexposed to the shock (i.e. is in "control group"). Therefore the effect of the DU update on county c can be written as

$$\beta_c = \beta \times \max\{DUshare_c - P_B(DUshare_c), 0\} \tag{6}$$

where $P_B(DUshare_c)$ denotes the B^{th} percentile of $DU\ Share_c$ across counties. Following prior literature (Gete & Reher, 2021), I report results for various definitions of control group as defined by B between 5% and 10%.

Assumption 2 (Partial Equilibrium) The effect of the DU update on aggregate mortgage approval rates is equal to the weighted sum of the county level effects β_c where the size of each mortgage market in terms of applications in 2016 are the weights, w_c. In particular, the share of observed mortgage approvals that is due to the DU update is

$$\eta = \frac{\sum_c w_c \times \beta_c}{\sum_c w_c \times (\mathit{Approval\ Rate}_{c,post} - \mathit{Approval\ Rate}_{c,pre})} \tag{7}$$

interaction channel independent of a lender being a non bank or not which would be ideal in disentangling between the two channels. Nonetheless, results presented in Table A.5 suggests that the securitization channel as proxied by high non bank involvement still persists for samples split by differing levels of loan officers per applicant in an area .

where $ApprovalRate_{c,pre}$ are $ApprovalRate_{c,post}$ are approval rates for conventional mortgages in county c for the period 2014 to 2016 and 2017 to 2019. Finally, the raw statistic in equation 6 is reweighed by a factor of 0.72 to reflect that 72% of all mortgage applications are conventional loans based on the HMDA data in the pre policy period year of 2016. This is because I calculate an aggregate effect for conventional loans only. Table 12 presents the results of the aggregation exercise. Focusing on column (1), the DU update accounts for between 32% and 36% of the increase in approval rates for conventional mortgages, which after appropriately weighting for conventional mortgage markets in column (2), accounts for between 23% and 26% of the increase in overall mortgage approval rates.

[Insert Table 12]

5.6 Who Benefits more from the DU Update?

5.6.1 Credit Access across Racial Groups

Prior research studies factors affecting credit access to under served communities [31]. In the context of mortgage lending, there is disparities in credit access for minorities (Giacoletti et al., 2022; Munnell et al., 1996). In this section, I study if the restrictions in the DU algorithm prior to the update had differential effects on certain groups, especially racial minorities more than others. There are at least two potential ways through which there could be differential impact of the policy on racial minorities. First, there might be systematically more racial minority applicants in the affected debt to income range so these group of applicants might benefit more from the DU policy. This is because they may be over leveraged due to other preexisting non mortgage debt as well as due to possibly having lower incomes. The other explanation would be that there is no systematic difference in distribution of racial minority applicants with regards to the debt to income, but rather a positive AUS recommendation has disproportionately more positive impact in extending credit to racial minorities. This may be because a positive AUS recommendation may help in alleviating concerns of creditworthiness if other observable, non debt to income aspects of the minority loan applicants is not sufficiently strong i.e. credit score. Moreover, a positive AUS

[31] For instance, while Célerier and Matray (2019) study the role of local financial development for low income households, Akey et al. (2021) study how political powers affects credit access in minority neighborhoods.

recommendation may even help to reduce the possibility of inherent biases against racial minorities (Bartlett et al., 2022), that is even when borrowers are identical but approval decision is based entirely on lender's own decision making criterion in absence of race-independent evaluation of borrowers from the AUS [32].

Thus, I explore whether the update to DU has differential effects across racial groups. In order to test this, I create a variable *High Minority* which equals one if a county is in the top quartile of the proportion of mortgage applicants who are not white in 2016 or zero otherwise. The estimates from columns (1) and (2) in table 13 shows that more mortgages were approved in counties with greater non-white borrowers after the DU update suggesting greater increases in credit access for racial minority borrowers.

[Insert Table 13]

5.6.2 Markets with Existing Frictions

In this section I explore whether the update to DU results in more benefit to borrowers in underserved markets. Quantitative models (e.g. Bemanke & Gertler, 1989) require borrowing constraints to generate amplified effects. In my setting of the US mortgage loan market, borrowing constrains will be intensified if borrowers face frictions in substituting to alternate loan types such as the Federal Housing Administration (FHA) loans when they are denied for standard conventional loans. Importantly, starting from 2011, many lenders pulled out from the market for FHA loans after being sued by HUD and Department of Justice under the False Claims Act for their FHA lending activity (Parrott & Goodman, n.d.). I hypothesize that markets where there was a greater share of FHA lending by litigated lenders will benefit more from such change in DU recommendations because of the greater potential void created in FHA lending in such markets.

I test whether conventional loan originations increased more in counties affected by the False Claims Act litigation after the DU update. I estimate equation 1 with the natural logarithm of conventional loan originations as the dependent variable. I create a variable *High False Claim* FHA_{2010} which equals one if a county was in the top quartile of FHA loan share by litigated lenders

[32] Given the data limitations of not observing debt to income alongside race and others observable attributes for loan application, disentangling between these alternative explanations is not feasible.

in 2010 or zero otherwise [33]. In column (1) of Table 14, we see that the coefficient on $DUShare \times Post$ is positive and statistically significant. Moreover, in columns (2) and (3) the coefficient of interaction terms is also positive and statistically significant. This result suggests that the DU recommendation shock benefited borrowers more from counties more affected by False Claims Act Litigation activity.

[Insert Table 14]

5.7 Real Effects

5.7.1 Implication for Housing Market

Given the increase in approval rate from the DU recommendation shock that I document, it is important to see whether this leads to real effects in the housing market. In particular, due to the update to DU, if marginal borrowers who are in need of credit the most are now able to avail mortgage credit, then it should be that it results in an increase in home ownership rates. In Panel A of Table 15, I formally test this by estimating equation 1 using the rate of owner occupied homes as the dependent variable. The results suggest that a county entire dependent on DU for underwriting mortgage loans will experience about a 2 percentage point increase in home ownership rate after the DU update.

[Insert Table 15]

Next an increase in owner occupied homes could lead to a lower demand for rentals (Gete & Reher, 2016). A lower demand for rentals can then lead to dampening of rent growth. In Panel B of Table 15, I test this using the annual growth in rent for a county as the dependent variable [34]. The results suggest a county entirely dependent on DU for mortgage underwriting experiences a 5 percentage point decrease in rent growth after the shock to DU recommendations[35]. These estimates for the growth in rent is similar to magnitudes in previous studies (e.g. Gete & Reher, 2018)[36].

[33]Information on lenders affected by the false claims act is collected from: https://buckleyfirm.com/sites/default/files/Updated-2021.10.04-Recent-FIRREA-Cases-Buckley-LLP.pdf

[34]The sample starts from 2015 due to data limitations.

[35]Table A.6 reports the effect on house prices from the DU update.

[36]In the specifications with all controls and fixed effects, I find that counties entirely reliant on DU experienced a 5

5.7.2 Crowding Out Effects

Does a shock affecting one type of credit crowd out another type of credit? For instance, shortciteschakraborty2018housingChakraborty, Goldstein, and MacKinlay (2018) find that banks active in strong housing markets react to housing price booms by reallocating commercial credit towards mortgage credit. Along the same lines, I test whether the update to DU leads to lenders crowding out commercial credit to private firms due to the increase in mortgage approval rates.

The premise underlying this crowding-out behavior is that lenders can be constrained in raising new capital. Such constraints can have real impact on lending opportunities, and may not be easily overcome especially by banks, which are comparatively less likely to be active in securitization markets. In order to formally test this, I estimate the following regression:

$$Y_{b,c,t} = \alpha + \beta(DUshare_b \times Post_t) + \gamma'\mathbf{X_{b,t}} + \eta_b + \psi_{c,t} + u_{c,t} \tag{8}$$

where $DUshare$ is the fraction of applications run through Desktop Underwriter by a bank in 2016. The dependent variable is the natural logarithm of the number or amount of CRA small business loans. Since, I only observe equilibrium loan originations, I control for demand side factors through county-year fixed effects. This allows me to compare lending by high DU reliant banks to low DU reliant banks lending to the same county in the same year (Khwaja & Mian, 2008). Table 16 presents the results[37]. In columns (1) to (3), there is a negative effect on logarithm of the number of CRA loans which is significant at the 10% level after controlling for bank level balance sheet characteristics and including bank size decile by year fixed effects. In columns (4) to (6) there is a negative effect on logarithm of CRA loan amount which is statistically significant at the 1% level across all columns. The evidence points to high DU reliant banks curtailing their small business lending, especially on the intensive margin after the DU update.

[Insert Table 16]

percentage point increase mortgage approval rates and 5% decrease in rent growth. So, a one percentage point increase in approval rate corresponds to a 1% decrease in rent growth. This is similar to Gete and Reher (2018) who find that a 1 percentage point increase in denial rates raises rent growth by 1.3 %.

[37]To shed further light on whether banks' constraints in raising capital plays a role in their small business lending, table A.7 presents results on samples split by capital constrained and unconstrained banks, in terms of size, deposits and leverage. The findings show that crowding out behavior of DU reliant banks is concentrated among those banks which are constrained i.e. smaller and more levered banks. Yet another mechanism behind this crowding out effect can be workforce capacity or personnel constraints. However, data limitations on individual banks' workforce related to lending activities prevents further exploration of this explanation.

The conservative coefficient estimate suggests that a lender which relies exclusively on DU for mortgage underwriting reduces small business lending by approximately by 25.5% in a county [38]. Given the median lender operates in 50 counties and lends about \$349000 in small business loans in a county, back of the envelope calculation suggests a decrease of $0.255 \times 50 \times 349000 =$ \$4449750 in small business lending. To put this number in perspective, prior to the DU policy the median lender received about 1442 mortgage applications with a loan amount of \$225000 and 94.5% of all approved loans eventually originated. Using the estimate on approval rate on the effect of the policy change from Table A.3 and that, this suggests an increase of about $1442 \times 0.073 \times 0.945 \times 225000 =$ \$22404105 in mortgage lending. This implies that for median lender the decrease in small business lending amount is about 20% of the increase in mortgage lending amount from the DU update.

6 Conclusion

In this paper, I study the effects of a policy change in automated mortgage underwriting in due cognizance of improved quality of borrower data. The pre-crisis period saw a deterioration in data reporting practices resulting in data inaccuracies which limited the effectiveness of algorithm based evaluation. Using confidential data on all mortgage applications run through a major automated underwriting system, Desktop Underwriter, I first document a discrepancy in how the system evaluated particular loan applicants. Prior to 2017 July, this system provided disproportionately more negative recommendations whenever the loan applicant's debt to income ratio was specifically between 45% and 50%. This was due to the undisclosed imposition of additional restricting factors to compensate for the inability for accurate risk assessments for such borrowers as data on income and components of debt were inaccurate and under-reported. However, immediately after a software update in the system in 2017 July which re-estimated the risk assessment and removed these compensating factors, such discrepancies in loan application evaluation disappeared. Such an update was enabled by the improved quality of borrower data in the post-crisis era. I then merge novel data on Desktop Underwriter usage to publicly available mortgage lend-

[38] I convert log points to implied percentage decrease following DeFusco (2018). So, the point estimate suggests a decrease $100 \times [e^{(-0.289-0.5(0.103)^2)} - 1] = 25.5\%$.

ing data and use this unique setting to study the causal effect of automated underwriting system recommendations in the mortgage market.

Exploiting regional variation in Desktop Underwriter usage across counties and its 2017 July software update as a plausibly exogenous positive shock to recommendations resulting in sudden variation in lending standards, I find that more exposed areas experience an increase in mortgage approval rates. Despite the rise in mortgage acceptance for credit seeking borrowers, I do not find evidence of a surge in credit risk. This suggests that there was no deterioration in borrower quality but rather many creditworthy borrowers were previously denied access to credit. Consistent with positive recommendations signalling a prospect for GSE purchase, the effect on credit acess is particularly pronounced where non bank lenders have greater market presence suggesting how lender incentives for mortgage securitization result in their response to recommendations. I also find that the effect is stronger where the scope of human interaction between borrower and lender is limited suggesting how a lack of both human discretion and alternative means of underwriting borrowers can impede credit access when exclusively relying on automated underwriting. Moreover, this shock to recommendations resulted in greater benefits to racial minorities and borrowers who faced frictions in substituting into alternate mortgage products due to the void left by litigated lenders in such markets. Turning downstream, I document an increased rate of owner occupied homes and a resultant positive spillover effect on housing affordability through lower growth in rents in the most exposed areas. However, as more exposed banks divert resources towards mortgage lending, it ends up crowding out their small business lending.

Since the most widely used automated underwriting systems are provided by government agencies, my results have important policy implications. First, rather than simply restricting borrowers based on a specific attribute (debt to income ratio in this case), underwriting systems can better utilize the improved quality of applicant data in the modern era in their algorithmic risk assessment models in order to better balance credit access and risk. Second, given the heterogeneity in response to the recommendation shock based on how lenders operate, any major change to underwriting systems should consider the differential consequences for borrowers in the mortgage market.

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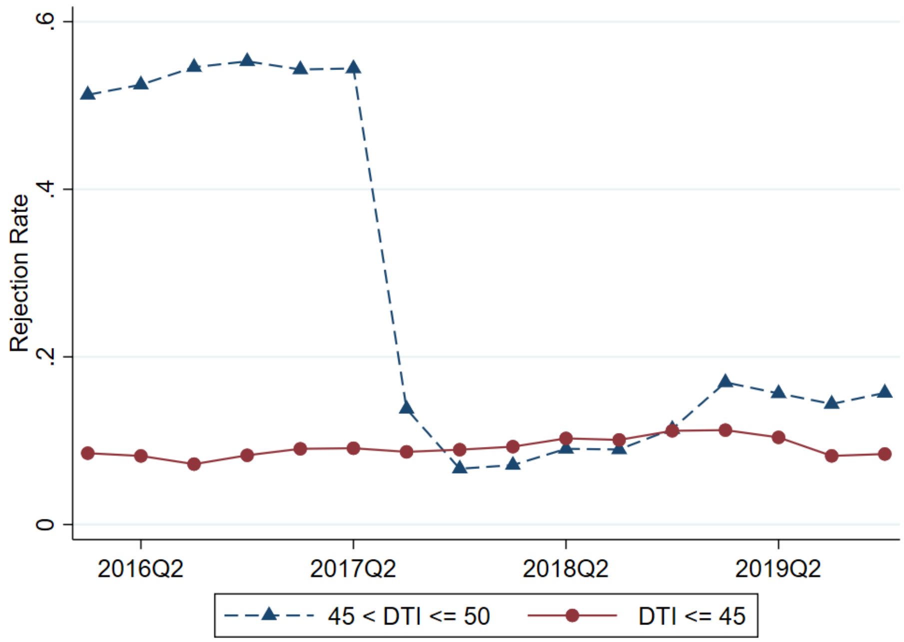

Figure 1: Desktop Underwriter Recommendation by Debt to Income

This figure plots the fraction of submitted loan applications which not did not receive an approve recommendation by debt to income groups. Source: Fannie Mae

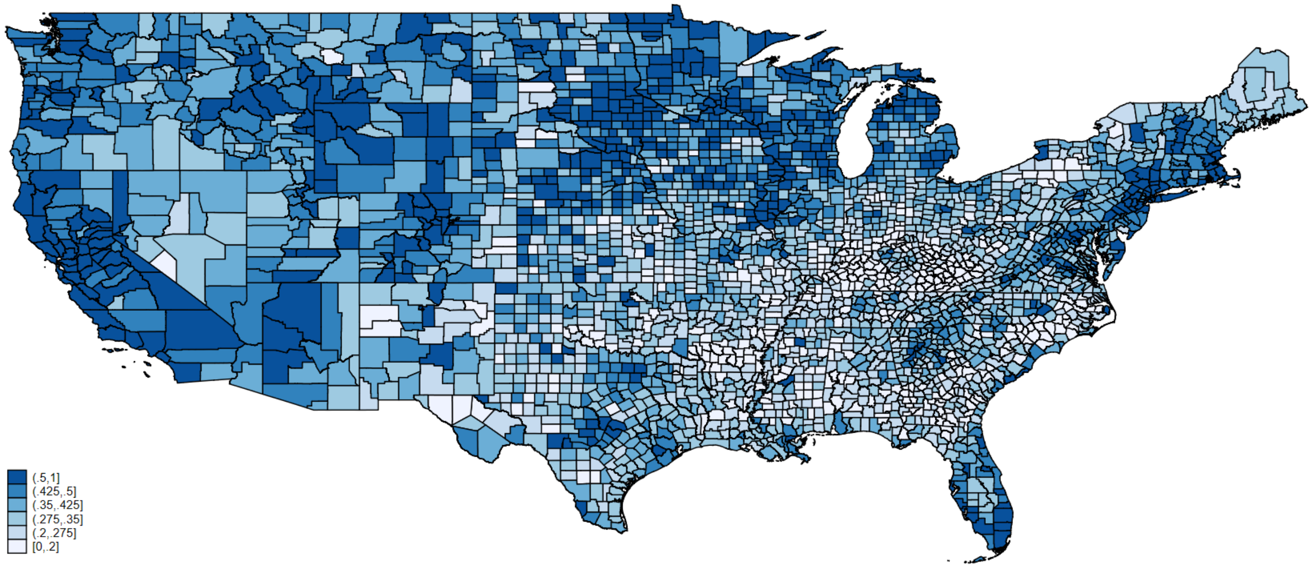

Figure 2: Spatial Heterogeneity in Desktop Underwriter Reliance

This figure plots the geographic distribution of the fraction of loan applications submitted through Desktop Underwriter across US counties in 2016. Source: HMDA, Fannie Mae

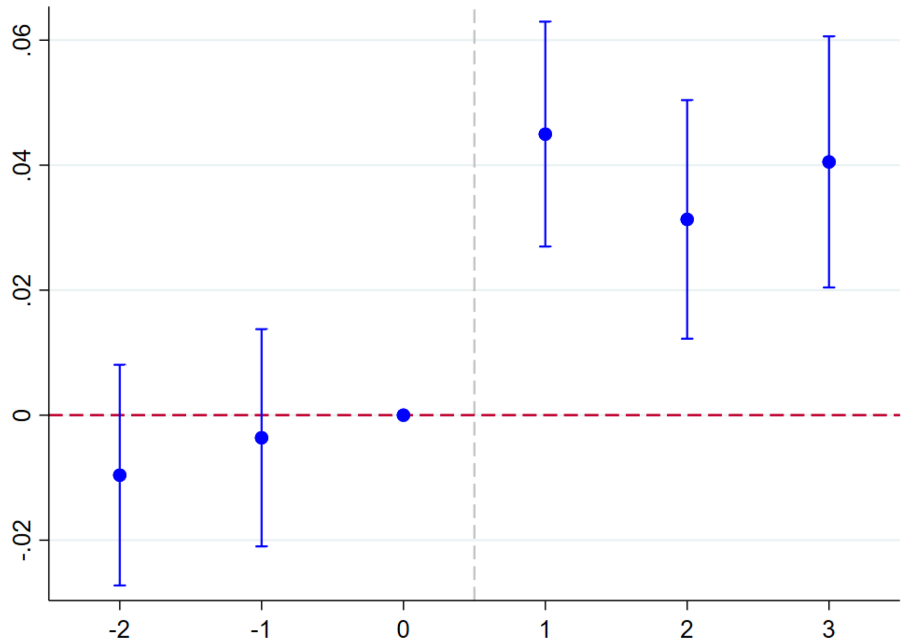

Figure 3: Event Study Estimates for Mortgage Approval Rate

This figure plots dynamic difference in difference coefficients estimates and the corresponding 95 percent confidence interval for the mortgage approval rate. The estimating equation is:

$$Y_{c,t} = \alpha + \sum_{t} \beta_t (DUshare_c \times Event_t) + \eta_c + \psi_{s,t} + u_{c,t}, \quad t \in \{-2, -1, 1, 2, 3\}$$

The sample period is from 2014 to 2019. The reference year is 2016 and so the interaction term in this pre treatment period is omitted. Robust standard errors are clustered at the county level. Source: HMDA, Fannie Mae

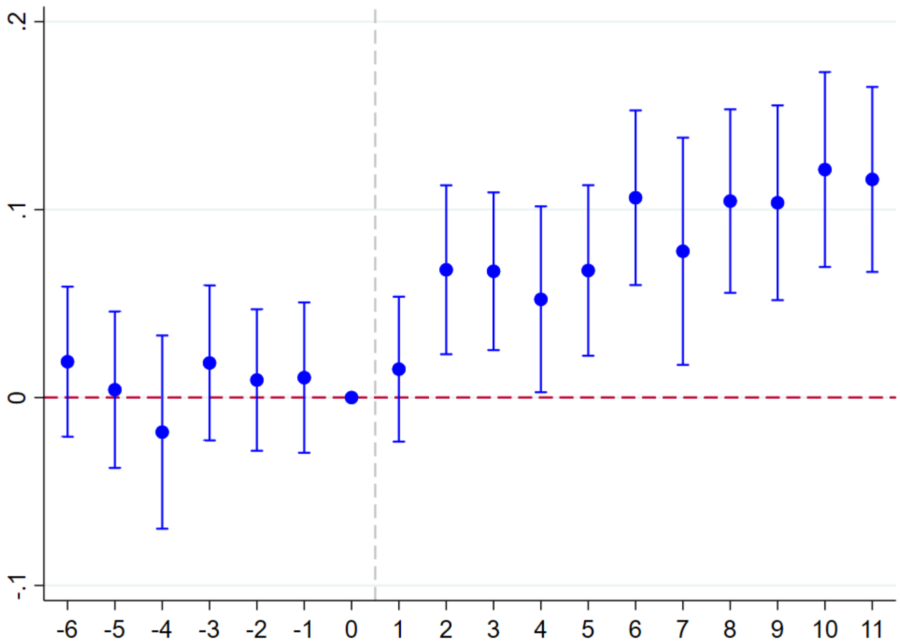

Figure 4: Event Study Estimates for affected debt to income loans

Note: This figure plots dynamic difference in difference coefficients estimates and the corresponding 95 percent confidence interval for the proportion of loans with debt to income over 45. The estimating equation is:

$$Y_{z,t} = \alpha + \sum_{t \neq 2017July} \beta_t (DUshare_z \times Event_t) + \eta_z + \psi_t + u_{z,t}$$

The sample period is from 2017 January to 2018 June. The reference month is 2017 July and so the interaction term in this pre treatment period is omitted. Robust standard errors are clustered at the 3 digit zip code level. Source: GSE Single Family data, HMDA, Fannie Mae

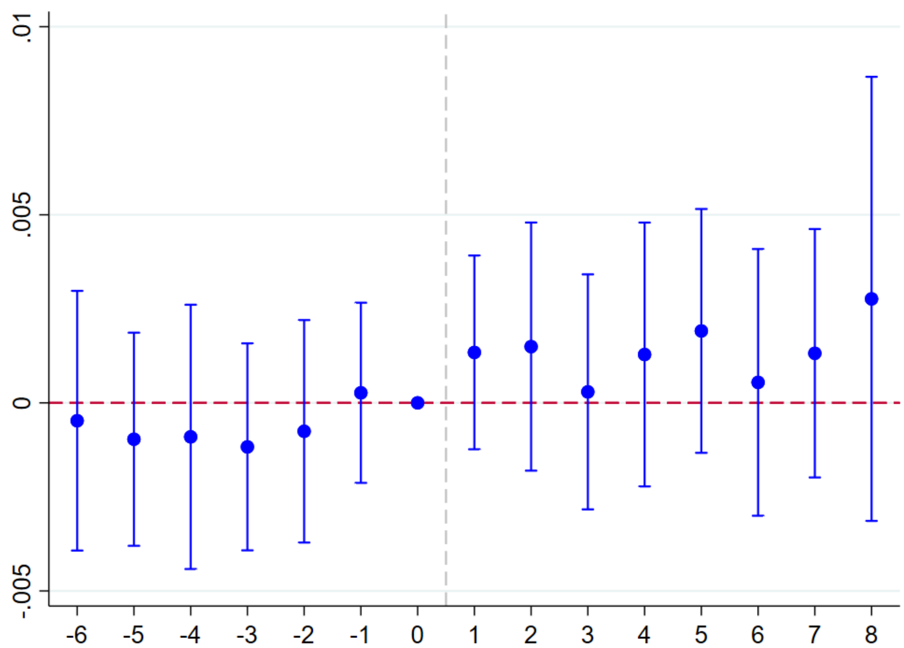

Figure 5: Event Study Estimates for delinquency in affected debt to income loans

This figure plots dynamic difference in difference coefficients estimates and the corresponding 95 percent confidence interval for the whether loans is delinquent in the 2 years following origination. The estimating equation is:

$$Y_{i,t} = \alpha + \sum_{t \neq 2017July} \beta_t (DTI > 45_{i,t} \times Event_t) + \gamma' \mathbf{X_{i,t}} + \eta_{LTV \times FICO} + \psi_{z,t} + u_{i,t}$$

The sample period is from 2017 January to 2018 March. The reference month is 2017 July and so the interaction term in this pre treatment period is omitted. Robust standard errors are clustered at the MSA level. Source: Fannie Mae Single Family data

Table 1: Summary Statistics

This table presents summary statistics of variables at the county level used in the main analysis over the period of 2014-2019. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *Originations* is the number of conventional loans originated in a county-year. *Median Income ('000s)* is median household income for the county in 000s. *Subprime Share* is the number of people per 100 people in a county with credit score below 660 and fraction of minority mortgage applicants. *Unemployment Rate* is the county unemployment rate in percentage points. *Dependency Ratio* is sum of child and old age dependency ratio. *Minority Share* is the number of non white mortgage applications divided by total mortgage applications. *Bank Share* is number of mortgage applications from traditional lenders divided by total number of mortgage applications.

	N	Mean	Std. Dev.	p10	p50	p90
DU Share	16787	0.35	0.13	0.19	0.35	0.54
Approval Rate	16787	0.75	0.10	0.61	0.77	0.86
Originations	16787	1791	5828	56	335	3934
Median Income ('000s)	16787	51.14	13.46	36.74	49.10	67.39
Subprime Share	16784	29.00	8.77	18.32	28.05	41.04
Unemployment Rate	16787	4.98	1.89	2.90	4.60	7.40
Dependency Ratio	16787	67.09	9.77	56.30	67.00	79.20
Minority Share	16787	0.19	0.12	0.08	0.16	0.34
Bank Share	16787	0.64	0.15	0.44	0.65	0.83

Table 2: Differences in county characteristics based on Desktop Underwriter Reliance

This table presents means and standard deviations of county economic variables for above and below median usage of Desktop Underwriter in 2016, the year before treatment. The last two columns reports the difference between two groups and the p values for tests of difference in means. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Median Income ('000s)* is median household income for the county in 000s. *Unemployment Rate* is the county unemployment rate in percentage points. *Dependency Ratio* is sum of child and old age dependency ratio. *Subprime Share* is the number of people per 100 people in a county with credit score below 660 and fraction of minority mortgage applicants. *Minority Share* is the number of non white mortgage applications divided by total mortgage applications. *Bank Share* is number of mortgage applications from traditional lenders divided by total number of mortgage applications. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	DU share < p50		DU share ≥ p50			
	Mean	Std. Dev.	Mean	Std. Dev.	Difference	p-value
Median Income ('000s)	43.62	(8.83)	55.67	(13.49)	-12.05	0.00***
Unemployment Rate	5.86	(1.79)	4.77	(1.71)	1.09	0.00***
Dependency Ratio	66.89	(8.11)	67.27	(11.18)	-0.38	0.30
Subprime share	33.99	(8.14)	24.57	(6.67)	9.42	0.00***
Minority Share	0.20	(0.14)	0.17	(0.09)	0.03	0.00***
Bank Share	0.64	(0.14)	0.63	(0.14)	0.01	0.19
Observations	1419		1420			

Table 3: Effect on Mortgage Approval

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate			
	(1)	(2)	(3)	(4)
DU share × Post	0.060***	0.061***	0.068***	0.050***
	(0.005)	(0.005)	(0.006)	(0.007)
County FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No
County Controls	No	No	Yes	Yes
State-Year FE	No	No	No	Yes
Observations	16787	16787	16784	16778
R^2	0.856	0.866	0.870	0.881

Table 4: Effect on Mortgage Approval in High Debt to Income areas

This table presents difference in differences estimates from equation 3. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Affected App share* is the share of loan applications in Desktop Underwriter with debt to income ratio between 45 and 50 in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate		
	(1)	(2)	(3)
DU share × Affected App share × Post	0.435***	0.414***	0.452***
	(0.066)	(0.087)	(0.080)
County Controls	Yes	Yes	Yes
County FE	No	No	Yes
State-Year FE	No	Yes	Yes
Observations	16784	16778	16778
R^2	0.540	0.608	0.881

Table 5: Robustness - Concurrent Regulatory Events

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. *Conforming Share* is the fraction of loan applications below the conforming loan limit. *Low English Population* equals 0 for years 2017 and before and it equals the share of limited English speaking Hispanic population for the year 2018 and it equals the sum of limited English speaking Hispanic and Chinese population for the year 2019. *Low English Household* is defined analogously for households. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Conforming Loan Limits	Approval Rate			
Exclude	None	None	New Conforming Loans	Loans over $410,000
	(1)	(2)	(3)	(4)
DU share × Post	0.048***	0.051***	0.046***	0.048***
	(0.007)	(0.007)	(0.007)	(0.007)
Conforming share	0.015*	0.006		
	(0.008)	(0.007)		
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	16781	16778	16778	16778
R^2	0.879	0.881	0.881	0.881

Panel B: FHFA Language Access Plan	Approval Rate			
	(1)	(2)	(3)	(4)
DU share × Post	0.043***	0.049***	0.043***	0.049***
	(0.007)	(0.007)	(0.007)	(0.007)
Low English Population	0.031	0.041*		
	(0.025)	(0.024)		
Low English Household			0.056	0.068*
			(0.038)	(0.037)
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	16781	16778	16781	16778
R^2	0.879	0.881	0.879	0.881

Table 6: Robustness - Shock to Funding Condition

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variables are either the natural logarithm or the per capita level of the market share weighted average deposits, lines of credit and total credit limit of lenders in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	ln(Deposit)	ln(Credit Lines)	ln(Credit Limit)	Deposit Per Capita	Credit Line Per Capita	Credit Limit Per Capita
	(1)	(2)	(3)	(4)	(5)	(6)
DU share × Post	-0.168	-0.083***	-0.804***	-0.004***	-0.000***	2.755
	(0.105)	(0.026)	(0.129)	(0.002)	(0.000)	(1.773)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16777	16753	16753	16777	16753	16753
R^2	0.704	0.697	0.211	0.802	0.898	0.009

Table 7: Robustness - Change in Applicant Pool

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variables measure the proportion of applications from borrowers who are either black, non white Hispanics, with income above the median income or with income above the per capita income in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

Proportion of Applicants:	Black	Hispanic Non White	Above Median Income	Above Per Capita Income
	(1)	(2)	(3)	(4)
DU share × Post	-0.002	-0.000	-0.030***	-0.024***
	(0.003)	(0.001)	(0.007)	(0.007)
County FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	16778	16778	16778	16778
R^2	0.977	0.439	0.781	0.789

Table 8: Effect on Credit Risk

Panel A presents difference in differences estimates from equation 7. The sample period is 2017 January to 2018 March where the dependent variable 𝟙 *Delinquent* is an indicator for whether a loan was every 90 day delinquent in the two years following origination. *DTI > 45* is an indicator which equals one for loans with debt to income between 45 and 50 and zero for loans with debt to income between 40 and 45. Loan level controls include interest rate, unpaid principal balance, loan term, mortgage insurance, loan purpose dummy, mortgage insurance dummy, first time home buyer dummy and occupancy status dummy. Robust standard errors are clustered at the MSA level and reported in parentheses. Panel B presents difference in differences estimates from equation 1 using monthly data. The sample period is 2014-2019. The dependent variable, *Delinquency Rate* is the percentage of mortgages which are at least 90 day delinquent in a county-month. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of one from 2017 August or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

Panel A: Loan Level	𝟙 Delinquent			
	(1)	(2)	(3)	(4)
DTI $>$ 45 $\times$ Post	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Loan Controls	Yes	Yes	Yes	Yes
LTV-FICO FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	No
DTI indicator	No	No	Yes	Yes
Zip-Month FE	No	No	No	Yes
Observations	602609	602609	602609	602227
R^2	0.016	0.016	0.016	0.024
Panel B: County Level	Delinquency Rate			
	(1)	(2)	(3)	(4)
DU share $\times$ Post	0.000	0.000	-0.000	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
County FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	No
County Controls	No	No	Yes	Yes
State-Month FE	No	No	No	Yes
Observations	33840	33840	33840	33120
R^2	0.713	0.829	0.846	0.902

Table 9: Effect on Credit Risk by Unemployment Rate changes

Columns (1) to (5) in this table presents difference in differences estimates from equation 7. The sample period is 2017 January to 2018 March. The dependent variable $\mathbb{1}$ *Delinquent* is an indicator for whether a loan was every 90 day delinquent in the two years following origination. The sample is either split based on quartiles of unemployment rate change or includes all loans. $DTI > 45$ is an indicator which equals one for loans with debt to income between 45 and 50 and zero for loans with debt to income between 40 and 45. Loan level controls include interest rate, unpaid principal balance, loan term, mortgage insurance, loan purpose dummy, mortgage insurance dummy, first time home buyer dummy and occupancy status dummy. Column (6) presents difference in differences estimates from equation 1 using monthly data over 2014 to 2019 period where the dependent variable, *Delinquency Rate* is the percentage of mortgages which are at least 90 day delinquent in a county-month. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. County controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. *Post* is an indicator variable which takes the value of one for months 2017 August or after (for years 2017 or after) in columns (1) to (5) (column (6)), and zero, otherwise. *High* Δ*UnempRate* is an indicator which equals one for MSAs (counties) in columns (1) to (5) (column (6)) in the top quartile of unemployment rate change or zero otherwise. Robust standard errors are clustered at the MSA (county) level in columns (1) to (5) (column (6)) and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	$\mathbb{1}$ Delinquent					Delinquency Rate
Sample:	Q1	Q2	Q3	Q4	All	All
	(1)	(2)	(3)	(4)	(5)	(6)
DTI > 45 × Post	0.004	0.001	0.000	0.001	0.002	
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	
DTI > 45 × Post × High ΔUnempRate					-0.003	
					(0.002)	
DU share × Post						0.001
						(0.003)
DU Share × Post × High ΔUnempRate						0.003
						(0.004)
Level of Analysis	Loan	Loan	Loan	Loan	Loan	County
Loan/County Controls	Yes	Yes	Yes	Yes	Yes	Yes
LTV-FICO FE	Yes	Yes	Yes	Yes	Yes	No
DTI indicator	Yes	Yes	Yes	Yes	Yes	No
County FE	No	No	No	No	No	Yes
Zip-Month FE	Yes	Yes	Yes	Yes	Yes	No
State-Month FE	No	No	No	No	No	Yes
R-squared	0.032	0.026	0.021	0.017	0.024	0.904
Observations	159666	139538	151412	151252	602227	33120

Table 10: Heterogeneous Effects by Securitization Incentives

This table presents difference in differences estimates from equation 1 modified with an interaction term. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. *High Non Bank* is an indicator variable which takes the value of 1 if the county is in top quartile in the share of non bank lenders in 2016 and 0 otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate	
	(1)	(2)
DU share × Post	0.034***	0.040***
	(0.008)	(0.008)
DU share × Post × High Non Bank	0.033**	0.036**
	(0.014)	(0.014)
High Non Bank × Post	-0.011*	-0.012**
	(0.006)	(0.006)
County FE	Yes	Yes
County Controls	No	Yes
State-Year FE	Yes	Yes
Observations	16781	16778
R^2	0.879	0.881

Table 11: Heterogeneous Effects by Borrower-Lender Interaction

This table presents difference in differences estimates from equation 1 modified with an interaction term. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. *Loan Officer - High* is an indicator variable which takes the value of 1 if the county belongs to a state in the top quartile of the number of loan officers per applicant in 2016 and 0 otherwise. *No Human - High* is an indicator variable which takes the value of 1 if a county is in the top quartile of the share of loans processed by lenders requiring no human interaction between lender and borrower in the application process in 2016 and 0 otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate			
	(1)	(2)	(3)	(4)
DU share × Post	0.052***	0.058***	0.029***	0.037***
	(0.008)	(0.009)	(0.007)	(0.007)
DU share × Post × Loan Officer - High	-0.029**	-0.029**		
	(0.014)	(0.014)		
DU share × Post × No Human - High			0.043***	0.041***
			(0.013)	(0.013)
County FE	Yes	Yes	Yes	Yes
County Controls	No	Yes	No	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	16781	16778	16781	16778
R^2	0.879	0.881	0.879	0.882

Table 12: Share of Growth in Mortgage Approval Rate due to the DU Shock

This table presents results of the implied contribution of the DU software update to the increase in aggregate mortgage approval rates over the period 2014-2019 around the DU policy change, denoted by η which is defined in Equation 6. Δ $Approval\ Rate$ is $ApprovalRate_{c,post} - ApprovalRate_{c,pre}$. The implied contribution is based on Assumption 1 (Control group) and Assumption 2 (Partial equilibrium). Each row makes a different assumption about which counties are not affected by the DU shock which is denoted B. The first and second rows respectively assume DU shock has no effect on counties where DU share of conventional applications in 2016, $DUshare_c$, is below the 5th or 10th percentile across counties. The first column summarizes this calculation for the sample of loans in this study, the conventional mortgage market, and the second column reweights the statistic by 0.72 to reflect the aggregate mortgage market.

	Δ Approval Rate	
Mortgages:	Conventional	All
Share due to Shock, B = 0.05	36%	26%
Share due to Shock, B = 0.10	32%	23%
Source of point estimate, β :	Table 3, Column 4	

Table 13: Effect on Racial Minority Borrowers

This table presents difference in differences estimates from equation 1 modified with an interaction term. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. *High Minority* is an indicator variable which takes the value of 1 if the county is in the top quartile of the share of non-white mortgage applicants in 2016 and 0 otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate	
	(1)	(2)
DU share × Post	0.034***	0.040***
	(0.008)	(0.008)
DU share × Post × High Minority	0.029**	0.035***
	(0.013)	(0.013)
High Minority × Post	-0.014**	-0.015***
	(0.005)	(0.005)
County FE	Yes	Yes
County Controls	No	Yes
State-Year FE	Yes	Yes
Observations	16781	16778
R^2	0.879	0.881

Table 14: Markets with Existing Frictions - False Claims Act

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variable, *log(Origination)* is the logarithm of the number of conventional loans originated in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of one if the year is 2017 or after, and zero, otherwise. *High False Claim* FHA_{2010} equals one if the county is in the quartile of the share of FHA loans by litigated lenders in 2010 or zero otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level respectively.

	log(Origination)		
	(1)	(2)	(3)
DU share × Post	0.224***	0.176***	0.203***
	(0.029)	(0.029)	(0.030)
DU share × Post × High False Claim FHA_{2010}		0.103*	0.105*
		(0.062)	(0.062)
High False Claim FHA_{2010} × Post		-0.010	-0.010
		(0.023)	(0.023)
County FE	Yes	Yes	Yes
County Controls	Yes	No	Yes
State-Year FE	Yes	Yes	Yes
Observations	16778	16781	16778
R^2	0.994	0.994	0.994

Table 15: Housing Market Implications

This table presents difference in differences estimates from equation 1. In Panel A, the sample period is 2014-2019 and the dependent variable, *Homeownership* is the share of homes which are owner occupied in a county-year. In Panel B, the sample period is 2015-2019 and the dependent variable, *Rent Growth* is the annual growth in rent for each county. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

Panel A:	Homeownership			
	(1)	(2)	(3)	(4)
DU share × Post	0.025***	0.026***	0.019***	0.017***
	(0.003)	(0.003)	(0.003)	(0.004)
County FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
County Controls	No	No	Yes	Yes
State-Year FE	No	No	No	Yes
Observations	16787	16787	16784	16778
R^2	0.976	0.976	0.977	0.978

Panel B:	Rent Growth			
	(1)	(2)	(3)	(4)
DU share × Post	-0.073***	-0.073***	-0.059***	-0.050***
	(0.008)	(0.008)	(0.009)	(0.012)
County FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes
County Controls	No	No	Yes	Yes
State-Year FE	No	No	No	Yes
Observations	1860	1860	1860	1820
R^2	0.366	0.392	0.408	0.429

Table 16: Effect on Small Business Lending

This table presents difference in differences estimates from equation 8. The sample period is 2014-2019. The dependent variables, *ln(CRA Number)* and *ln(CRA Amount)* are the natural logarithm of the number and dollar amount of CRA small business loans by a bank in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter by a bank in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Bank level control variables are as follows. *Ln(Asset* is the natural logarithm of assets, *Deposit Ratio* is deposits by assets, *Equity Ratio* is total equity by assets, *Net Income Ratio* is net income by assets, *NIM Ratio* is net interest margin by assets and *Cash Ratio* is cash divided by assets. Robust standard errors are clustered at the bank level and reported in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level respectively.

	log(CRA Number)			log(CRA Amount)		
	(1)	(2)	(3)	(4)	(5)	(6)
DU share× Post	-0.088	-0.115	-0.112*	-0.301**	-0.289***	-0.295***
	(0.080)	(0.070)	(0.068)	(0.133)	(0.103)	(0.105)
log(Asset)			0.127			-0.007
			(0.114)			(0.203)
Deposit Ratio			0.037			0.756
			(0.353)			(0.942)
Equity Ratio			-0.225			-0.388
			(1.327)			(1.588)
Net Income Ratio			-3.378			-7.276
			(3.154)			(5.987)
NIM Ratio			3.155			3.466
			(3.558)			(5.354)
Cash Ratio			0.107			0.341
			(0.369)			(0.705)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Size-Year FE	No	Yes	Yes	No	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	91986	91986	91986	91901	91901	91901
R^2	0.089	0.091	0.091	0.340	0.341	0.341

APPENDIX

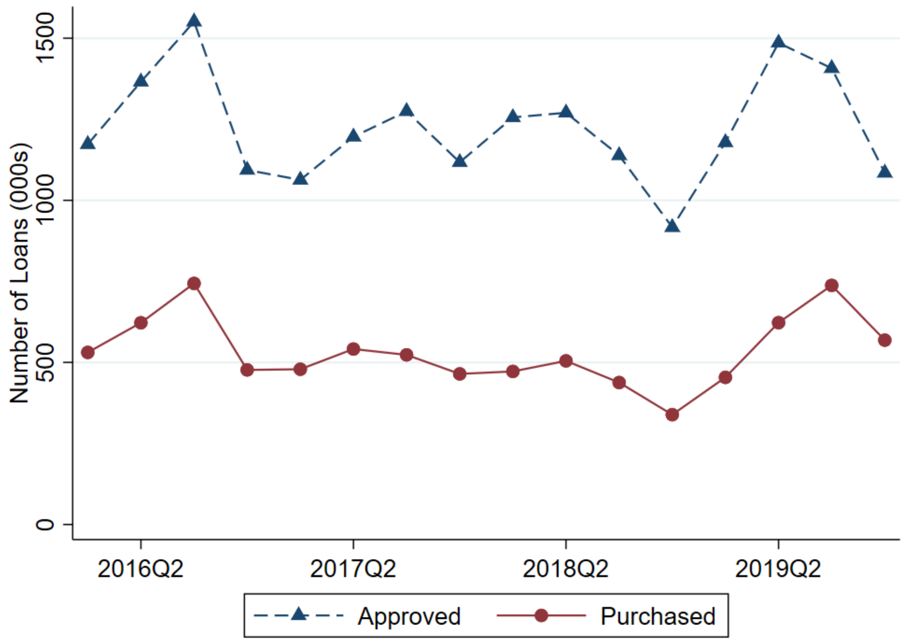

Figure A.1: DU Approved and Fannie Mae Purchases

This figure plots the number of all applications run through Desktop Underwriter which are approved and the number of mortgages purchased by Fannie Mae. Data sources: Fannie Mae

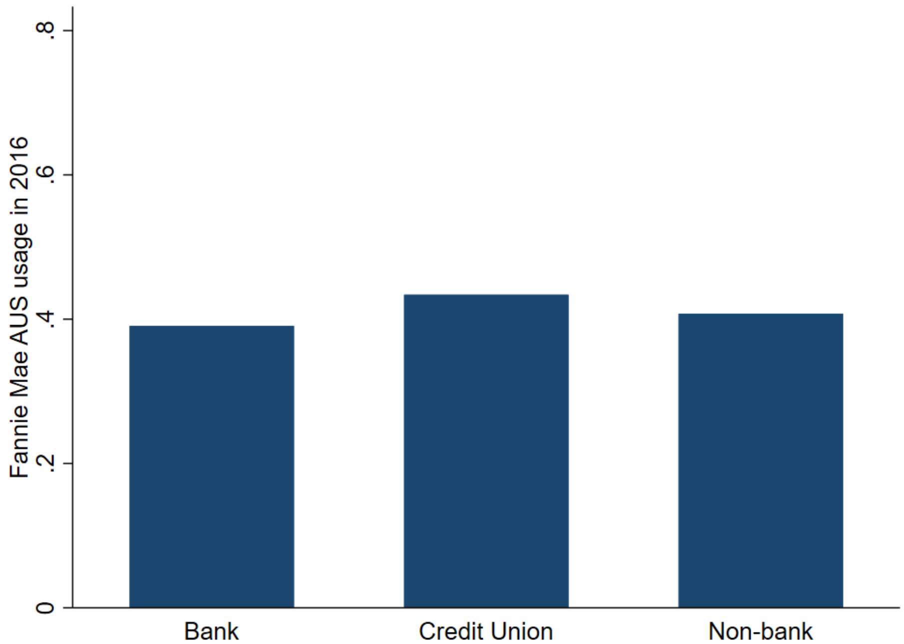

Figure A.2: Desktop Underwriter Usage by type of lender

This figure plots the share of all applications run through Desktop Underwriter for traditional banks, credit unions and non bank lenders in 2016. Data sources: Fannie Mae, HMDA

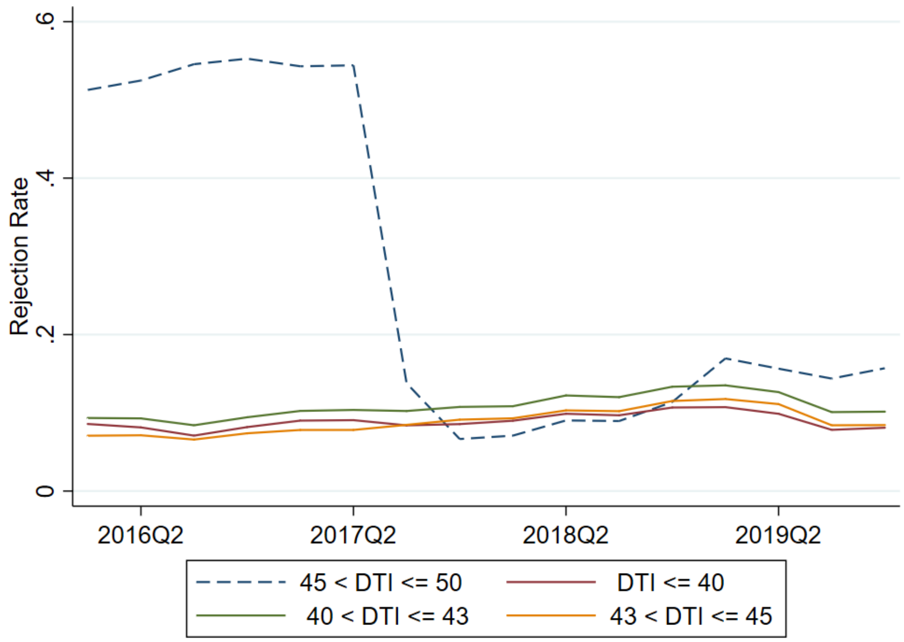

Figure A.3: Desktop Underwriter Recommendation by Debt to Income

This figure plots the fraction of submitted loan applications which not did not receive an approve recommendation by debt to income groups. Source: Fannie Mae

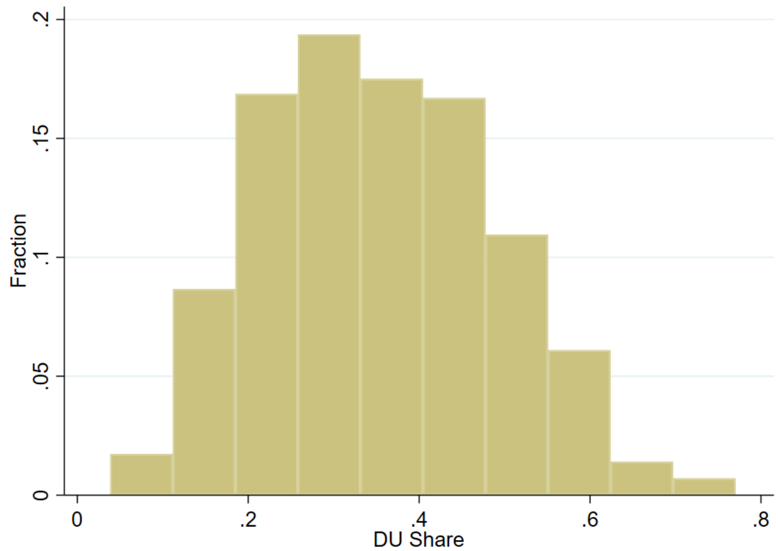

Figure A.4: Desktop Underwriter Reliance Density Distribution

This figure plots the distribution density of Desktop underwriter reliance where DU share is measured as the fraction of loan applications submitted through Desktop Underwriter across US counties in 2016. Source: HMDA, Fannie Mae

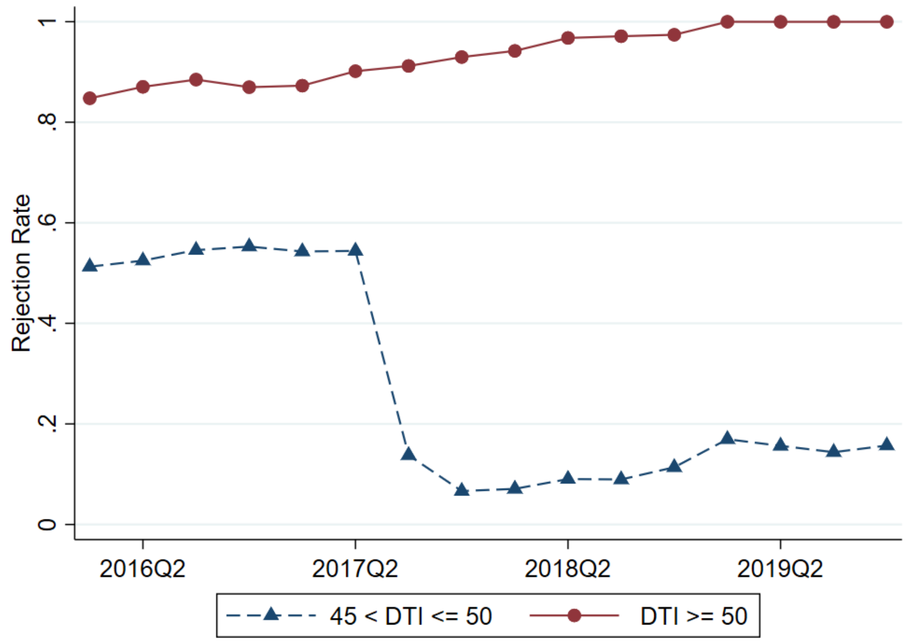

Figure A.5: Desktop Underwriter Recommendation by Debt to Income

This figure plots the fraction of submitted loan applications which not did not receive an approve recommendation by debt to income groups. Source: Fannie Mae

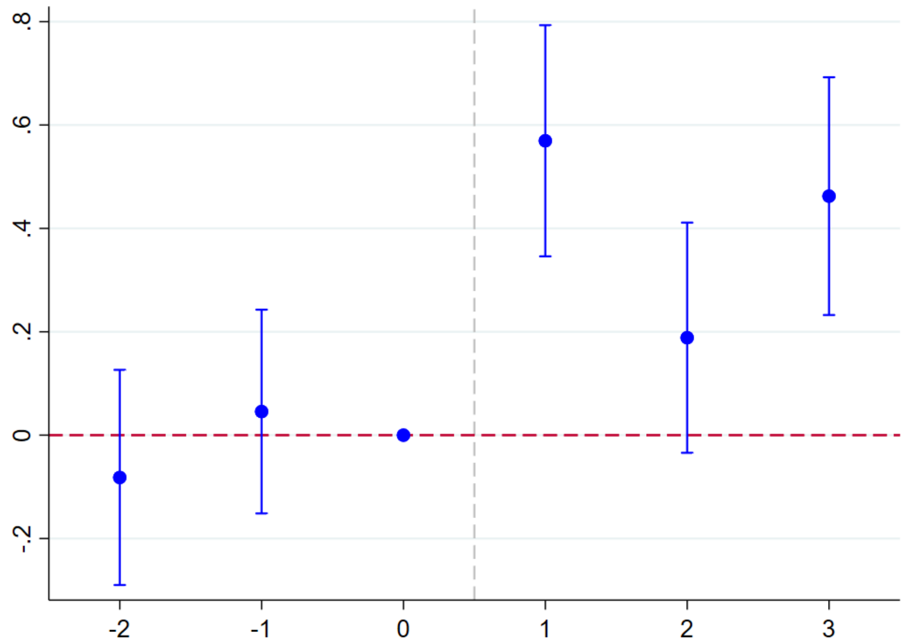

Figure A.6: Event Study Estimates for Mortgage Approval Rate

This figure plots dynamic difference in difference coefficients estimates and the corresponding 95 percent confidence interval for the mortgage approval rate. The estimating equation is:

$$Y_{c,t} = \alpha + \sum_{t} \beta_t (DUshare_c \times Affected\ App\ share_c \times Event_t) + \eta_c + \psi_{s,t} + u_{c,t}, \quad t \in \{-2, -1, 1, 2, 3\}$$

The sample period is from 2014 to 2019. The reference year is 2016 and so the interaction term in this pre treatment period is omitted. Robust standard errors are clustered at the county level. Source: HMDA, Fannie Mae

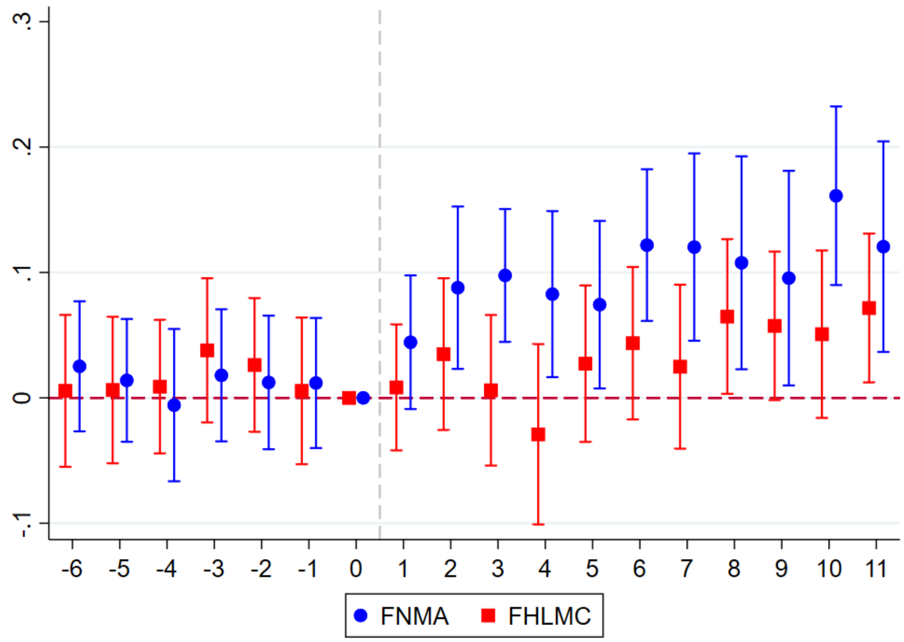

Figure A.7: Event Study Estimates for affected debt to income loans

Note: This figure plots dynamic difference in difference coefficients estimates and the corresponding 95 percent confidence interval for the proportion of loans with debt to income over 45 for Fannie Mae and Freddie Mac separately. The estimating equation is:

$$Y_{z,t} = \alpha + \sum_{t \neq 2017July} \beta_t (DUshare_z \times Event_t) + \eta_z + \psi_t + u_{z,t}$$

The sample period is from 2017 January to 2018 June. The reference month is 2017 July and so the interaction term in this pre treatment period is omitted. Robust standard errors are clustered at the 3 digit zip code level. Source: GSE Single Family data, HMDA, Fannie Mae

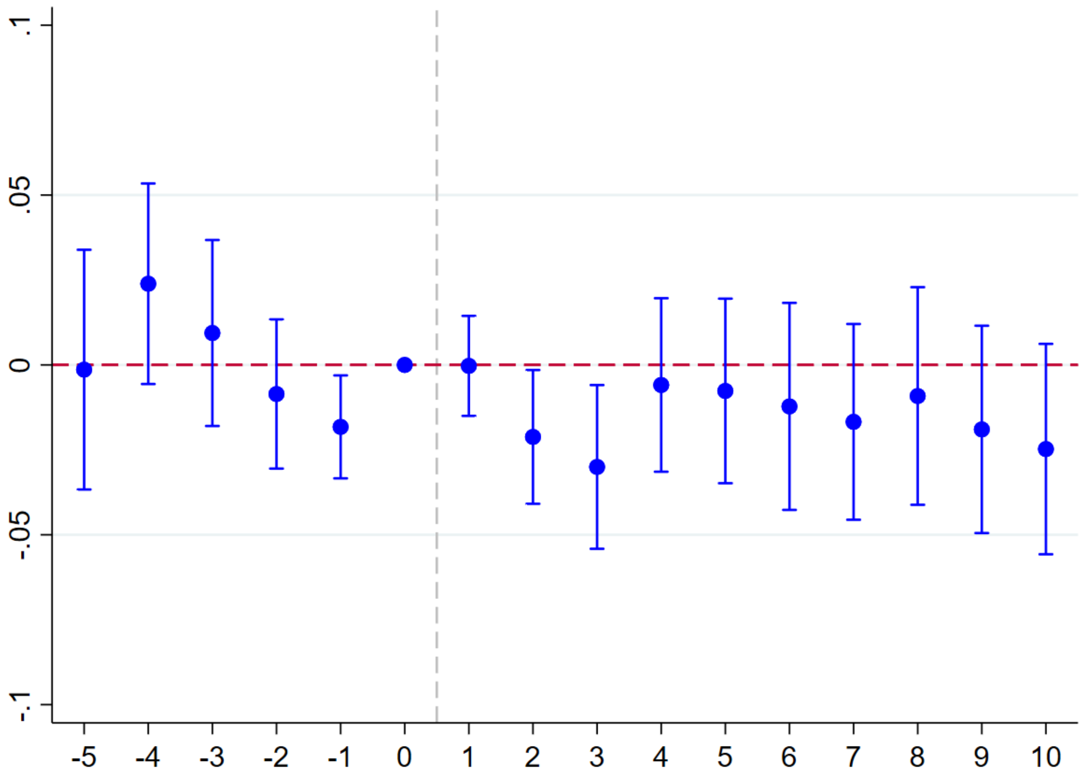

Figure A.8: Event Study Estimates for delinquency rate

Note: This figure plots dynamic difference in difference coefficients estimates and the corresponding 95 percent confidence interval for the county level delinquency rates. The estimating equation is:

$$Y_{c,t} = \alpha + \sum_{t \neq 2017Q2} \beta_t (DUshare_c \times Affected\ App\ share_c \times Event_t) + \eta_c + \psi_{s,t} + u_{c,t}$$

The sample period is from 2016 January to 2019 December. The reference period is second quarter of 2017 and so the interaction term in this pre treatment period is omitted. Robust standard errors are clustered at the county level. Source: CFPB, HMDA, Fannie Mae

Table A.1: Robustness - Differential Trends in Economic Activity

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. *Rural* takes the value of 1 for counties designated as rural by the CFPB and 0 otherwise. *High Income*, *High UnempRate* and *High Subprime* takes the value of 1 for counties with median household incomes above median, counties with unemployment rates above median, counties with subprime share above median and 0 otherwise. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate			
	(1)	(2)	(3)	(4)
DU share × Post	0.047***	0.045***	0.049***	0.053***
	(0.007)	(0.007)	(0.007)	(0.008)
Rural × Post	-0.005***			
	(0.002)			
High Income × Post		0.004**		
		(0.002)		
High UnempRate × Post			-0.001	
			(0.002)	
High Subprime × Post				0.005**
				(0.002)
County FE	Yes	Yes	Yes	Yes
County Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Observations	16778	16778	16778	16778
R^2	0.881	0.881	0.881	0.881

Table A.2: Evidence from GSE purchase data

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variable, *Share DTI > 45* is the share of GSE purchases with debt to income over 45 in a zip-month (zip-year) in columns (1) and (2) (columns (3) and (4)). *DU share* is the share of loan applications submitted through Desktop Underwriter in a zip code in 2016. *Post* is an indicator variable which takes the value of one for months August 2017 or after (if the year is 2017 or after), and zero, otherwise in columns (1) and (2) (columns (3) and (4)). Controls are time varying variables at the zip code level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the zip code level and reported in parentheses. *, **, *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Share DTI > 45			
Sample:	Monthly		Yearly	
	(1)	(2)	(3)	(4)
DU share × Post	0.056***	0.059***	0.046***	0.040**
	(0.009)	(0.009)	(0.016)	(0.017)
Zip FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Month FE	No	Yes	No	No
Year FE	No	No	No	Yes
Observations	15820	15820	5308	5308
R^2	0.604	0.642	0.748	0.886

Table A.3: Robustness - Lender Level Analysis

This table presents difference in differences estimates from equation 4. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of approved mortgage applications divided by the total number of completed mortgage applications for a lender-year. *DU* equals one if a lender used DU in 2016 or zero otherwise. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. The sample includes lenders with at least 1000 loan applications each year. Controls include number of loan applications and the lender level average of median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Observations are weighted by the lender's market share. Robust standard errors are clustered at the lender level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate	
	(1)	(2)
DU × Post	0.074**	0.073**
	(0.032)	(0.031)
Controls	Yes	Yes
Lender FE	Yes	Yes
Year FE	No	Yes
Observations	2484	2484
R^2	0.835	0.837

Table A.4: Effect on Interest Rates

This table presents difference in differences estimates from equation 7. The sample period is 2017 January to 2018 March. The dependent variable *Interest Rate* is mortgage interest rate during origination. *DTI > 45* is an indicator which equals one for loans with debt to income between 45 and 50 and zero for loans with debt to income between 40 and 45. Loan level controls include unpaid principal balance, loan term, mortgage insurance, loan purpose dummy, mortgage insurance dummy, first time home buyer dummy and occupancy status dummy. Robust standard errors are clustered at the MSA level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Interest Rate			
	(1)	(2)	(3)	(4)
DTI > 45 × Post	0.020***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
Loan Controls	Yes	Yes	Yes	Yes
LTV-FICO FE	Yes	Yes	Yes	Yes
Month FE	No	Yes	Yes	No
DTI indicator	No	No	Yes	Yes
Zip-Month FE	No	No	No	Yes
Observations	602609	602609	602609	602227
R^2	0.552	0.580	0.580	0.601

Table A.5: Heterogeneous Effects by Securitization Incentives

This table presents difference in differences estimates from equation 1 modified with an interaction term for different samples of level of Human interaction as measured by number of loan officers per applicant. The sample period is 2014-2019. The dependent variable, *Approval Rate* is the number of lender approved mortgage applications divided by the total number of completed mortgage applications in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. *High Non Bank* is an indicator variable which takes the value of 1 if the county is in top quartile in the share of non bank lenders in 2016 and 0 otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	Approval Rate		
Sample:	Full	Top 2 tercile of Loan Officers per Applicant	Top 1 tercile of Loan Officers per Applicant
	(1)	(2)	(3)
DU share × Post	0.040***	0.036***	0.029***
	(0.008)	(0.009)	(0.010)
DU share × Post × High Non bank	0.036**	0.042**	0.048*
	(0.014)	(0.019)	(0.025)
High Non bank × Post	-0.012**	-0.017**	-0.015
	(0.006)	(0.007)	(0.010)
County FE	Yes	Yes	Yes
County Controls	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes
Observations	16778	10957	7083
R^2	0.881	0.875	0.859

Table A.6: Effect on House Price

This table presents difference in differences estimates from equation 1. The sample period is 2014-2019. The dependent variable is *HPI* which is the house price index with base year of 2000 in a county or is *Home Value* which is the median home value in a county. *DU share* is the share of loan applications submitted through Desktop Underwriter in a county in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Controls are time varying variables at the county level and include median household income, unemployment rate, fraction of population with credit score below 660 and fraction of minority mortgage applicants. Robust standard errors are clustered at the county level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	HPI	Home Value
	(1)	(2)
DU share × Post	19.797***	47.644***
	(1.617)	(3.493)
County FE	Yes	Yes
County Controls	Yes	Yes
State-Month FE	No	Yes
State-Year FE	Yes	No
Observations	14128	198171
R^2	0.967	0.991

Table A.7: Effect on Small Business Lending - Bank Constraints

This table presents difference in differences estimates from equation 8. The sample period is 2014-2019. The dependent variables, *ln(CRA Number)* and *ln(CRA Amount)* are the natural logarithm of the number and dollar amount of CRA small business loans by a bank in a county-year. *DU share* is the share of loan applications submitted through Desktop Underwriter by a bank in 2016. *Post* is an indicator variable which takes the value of if the year is 2017 or after, and zero, otherwise. Banks are classified as unconstrained if they are in the top tertile by assets, deposits or equity to asset ratios, otherwise they are classified as constrained. Bank level control variables are as follows. *Ln(Asset* is the natural logarithm of assets, *Deposit Ratio* is deposits by assets, *Equity Ratio* is total equity by assets, *Net Income Ratio* is net income by assets, *NIM Ratio* is net interest margin by assets and *Cash Ratio* is cash divided by assets. Robust standard errors are clustered at the bank level and reported in parentheses. * , ** , *** denote statistical significance at the 10%, 5% and 1% level respectively.

	ln(CRA Number)						ln(CRA Amount)					
	Size		Deposit		Leverage		Size		Deposit		Leverage	
Constrained:	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Bank DU × Post	-0.201***	0.296**	-0.227***	0.245*	-0.268***	0.281***	-0.236***	-0.084	-0.346***	-0.102	-0.371***	0.184
	(0.074)	(0.138)	(0.079)	(0.137)	(0.087)	(0.095)	(0.076)	(0.318)	(0.088)	(0.290)	(0.097)	(0.133)
Z-test												
(Constr. = Unconstr.)	3.163***		2.991***		4.248***		0.462		0.805		3.375***	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Size-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	49740	38559	51997	36263	45365	42800	49671	38541	51930	36246	45296	42781
R^2	0.072	0.133	0.075	0.124	0.077	0.086	0.233	0.405	0.252	0.408	0.364	0.298