Stress testing on credit supply

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Abstract. *This study shows how post-crisis stress tests have affected the supply of home equity business loans. Stress tested banks reduce their loan originations but in terms of purchased loans, this effect is much stronger among stress tested banks that failed the exercise compared to other groups of banks. The magnitude of these effects is inversely proportional to the size of the loans. Even though the aggregate level of credit supply is relatively unchanged, within each size category of loans adopted in this study, growth rates are directly proportional to its origination size. The loan distributions significantly differ among stress-tested and non-stress-tested banks and there are significant geographical shifts in loan originations both by categories of banks and size of loans.*

Keywords: Banking, Stress testing, Credit supply, Home-equity loans

1. Introduction

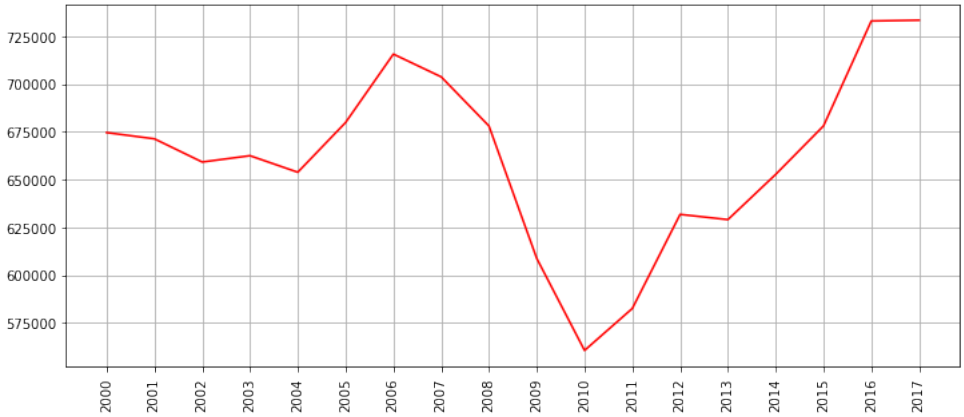
Large banks have been using internal stress tests since the 1990s; however, until 2007, these tests were typically performed only by the banks themselves as internal self-assessments [1]. The practice of using stress tests to evaluate trading portfolios was formalised in the 1996 market risk amendment to Basel I [2]. Since 2007, governmental regulatory bodies have resorted to conducting their own stress tests to ensure effective operation of their financial systems. Stress tests have been routinely performed by financial regulators in different countries to prevent banks under their authority from engaging in practices that can create financial contagion. Stress tests are now widespread. Regulatory bodies such as the European Banking Authority (EBA) and the International Monetary Fund (IMF) ensure that financial institutions have adequate capital allocations to cover potential losses during extreme, but plausible, events. Stress testing models typically not only allow testing of individual stressors, but also combinations of different events, or a know historical scenario.

Sector-wide stress tests differ largely in their design and implementation. A comparison of country practices shows that authorities design stress tests in different ways, with some employing more than one type of test [3]. To better understand these differences and their drivers, the Financial Stability Institute (FSI) conducted a comparative analysis, for which much information was gathered from selected authorities across the globe [3] covering a significant part of the banking sector in the Euro area, Japan, Switzerland, and the United States. Approaches to stress-testing and measure of capital adequacy have also been suggested in the academic literature [4, 5, 6].

Although stress tests are a powerful tool for understanding conditions in the banking sector, or of individual banks, the validity of their results is affected by a number of factors, such as data quality and availability, model risk and models' capacity to capture contagion effects and interlinkages, both within the banking sector and beyond [3]. Moreover,

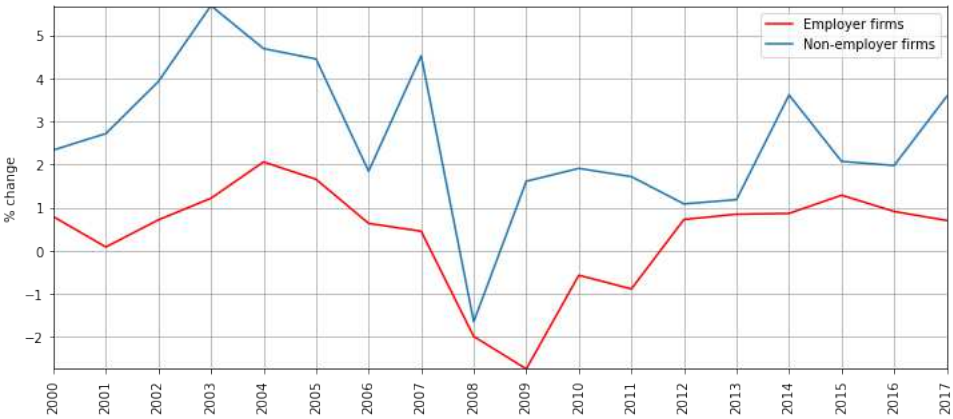
stress tests are known to have spillovers in the economy. Regulation, which may also include stress testing, is an especially common explanation among researchers when describing the slow recovery of small business lending (see e.g. [7, 8, 9, 10]). There is also a large literature suggesting that banks facing regulatory capital constraints cut their lending supply, and that stress tests create a direct link from bank lending risk to capital [11, 12, 13, 14].

Figure 1. Number of US startups $<$ 1 year 2000-2017



Source: Statista

Figure 2. Number of US small business annual % change 2000-2017



Source: Statista

There were 440 bank failures in the U.S. between 2009-2012 [1]. Data from the Mortgage Bankers Association (MBA) show that bank originations of business loans fell by as much as 39% in the year following the crisis. Fig 2 depicts a clear structural shift in the growth of small businesses before and after 2008. A 2019 report from CB Insights [2], states that, after lack of markets, insufficient financing is the second biggest reason for the failure of start-ups. Fig 1 shows the number of start-ups in each year that are under one-year old. Although they have been consistently increasing since the trough in 2010, the number

[1] https://www.fdic.gov/bank/historical/bank/

[2] https://www.cbinsights.com/reports/The-20-Reasons-Startups-Fail.pdf

of start-ups which have endured longer than three years is quite small. According to the European Association of Business Angels, 50 million new projects are launched every year (137,000 per day), but 90% of them fail. Another study by [15] on a sample of 214 failed start-ups, finds that 58% were unsuccessful in the first three years, and 86% failed within five years of business.

In this study we analyse how stress testing has affected Home Equity loans for business finance, as it is an important source of funding for start-ups and small businesses. We assume that stress tested banks that were adequate in the exercise do not decrease their holdings of business loans significantly compared to their non-stress tested counterparts. We also hypothesise that the effect sizes are smaller with larger loans, and that most of the cutbacks in originations and purchases are from the banks that failed the stress test, or whose plans were conditionally objected.

In the U.S., the time period, 2000-2008 and 2008-2014, are marked by continuous economic disequilibrium, the former through an unnatural rise in the housing market, and the latter through a strong fall. The centre of the two periods indicates a strong reversal in expectations of the housing market and the economy; this reversal in expectation had an impact on origination and purchase volumes of the banks. However, given the current state of recovery rate and post-crisis loan growth, we want to test whether stress tests have led banks to reduce their lending of smaller loans. Furthermore, in particular, we assume that banks have reduced their lending of HE business loans under $0.25m, but the level of reduction differ, depending on whether the bank passed the ST, failed the ST, or did not go through the ST. We assume considerable differences among these three categories of banks also in terms of loan purchase activities. Using data from Home Mortgage Disclosure Act (HMDA) and Federal Deposit Insurance Corporation (FDIC), we test the above hypotheses in the U.S. HE mortgage market. Section 2 provides a brief overview of regulatory testing and the CCAR exercise. A literature review on outcomes and spillovers of stress tests is given in section 3, followed by an explanation of the data and its sources in section 4, together with an exploratory analysis using the same data. Section 5 explains the methodology and discussion of results; and lastly, we give concluding remarks and policy recommendations in section 6.

2. Stress testing in the US

Comprehensive Capital Analysis and Review (CCAR) stress testing is a regulatory framework introduced by the U.S. Federal Reserve to assess, regulate and supervise large banks and financial institutions – collectively referred to as bank holding companies (BHCs). Annual assessment also includes the Dodd-Frank Act Stress Tests (DFAST), which are required by the Dodd-Frank Act (DFA). DFAST requires institutions to conduct and submit the results of stress test assessments and disclose them to the public. The assessment is designed to provide regulators with forward-looking information to aid banking supervision whilst also reassuring the U.S. public of the resilience of its economy should another financial crisis occur. with severely adverse scenarios featuring a deep recession characterized by a substantial increase in the unemployment rate, large declines in asset prices, and increases in risk premia.

While CCAR and DFAST are similar in their aims, the main differences relate to the size

of the institution to which these regulations apply. CCAR is used solely to assess the planning processes of larger institutions with assets exceeding $10 billion. the DFAST requirements by a considerable amount but do not apply to any banking organizations with assets of $10 billion or less. Another difference is that when the results are disclosed, there are no supervisory actions applicable to the DFAST. Nevertheless, the BHCs must consider their results in their capital planning. Whereas in CCAR, if a BHC fails the stress test, the Federal Reserve can object to their capital plans. An objection can be based on either qualitative or quantitative factors, e.g., if the projected capital ratio falls below the minimum requirement, or if qualitative vulnerabilities are detected in the governance structure and risk management. The minimum regulatory requirements are as follows:

- common equity tier 1 (CET1) ratio of 4.5%
- minimum tier 1 capital ratio of 6%
- total capital (considering both tier 1 & tier 2 capital) ratio of 8%
- leverage ratio of 4%
- supplementary tier 1 leverage ratio (for banks classified as advanced approach institution [3]) of 3%
- capital conservation buffer of 2.5% that if violated restricts the amount of capital that can be distributed
- counter cyclical capital buffer for advanced approaches banks

For an institution, if any one of the capital ratios mentioned above is projected to drop below a specified threshold following a severely adverse economic shock, they are considered to have failed the stress test. Such an institution is expected to limit its capital distributions and/or raise more capital to be better prepared for a severe scenario. Banks can differ from each other in terms of their loan type specialisation/portfolio, and thus so do the exposures of these loans to an assumed economic shock. Given that the level of capital buffers and its maintenance also differ among banks, passing a stress test may therefore depend on business models [16].

3. Literature review

The great recession reduced the ability of the market participants to secure credit. [17] find that banks with large losses from the crisis cut back the most on small business lending, but other banks took the opportunity to expand their market share [4]. By exploiting geographic variation across counties, [20] concluded that declines in larger home prices in 2007-09 caused larger reductions in local employment in non-tradable industries exposed to shifts in local consumption demand. However, declines had relatively little impact on employment in tradeable industries that were less exposed to local demands. In contrast [10] suggest that the credit supply shock from the four leading BHCs impacted more strongly on local employment in tradable industries. While [10] documents distinct findings, both analyses show the same underlying cause as the top four BHCs, which were

[3] A company is defined as an advanced approaches institution under federal regulatory capital rules if it has consolidated total assets of $250 billion or more, on-balance-sheet foreign exposure of $10 billion or more, or is a subsidiary of a depository institution that uses the advanced approaches to calculate total risk-weighted assets.

[4] In normal times, competition for borrowers is hindered by adverse selection, but when banks experience a negative shock, the information gap is reduced, facilitating lender substitution [18, 19]-in Bord et al (2018)

also largely responsible for overdriving their credit supply prior to 2007. Consequently, these 4 were also forced to tighten their lending standards or cutback on their lending amounts compared to other banks [21].

Study by [22] indicates that BHCs that encounter larger stress test shocks move strategically with their pricing, e.g., by reducing interest rates on their borrowers with higher-credit scores/incomes; and giving more cash rewards to lower-credit/income borrowers. In terms of home equity loans/credits, the authors confirm that higher capital shocks are associated with decreased overall mortgage credit quantities, driven primarily by a reduction in the number of new loans originated while the average mortgage loan amount originated and interest rates are higher. [9] report a decrease in home-equity loans or collateral secured loans compared to unsecured loans with stress tested (ST) banks, thereby cutting business-related home equity lending by around 30% more than non-stress-tested banks during the stress testing period. Similarly, [23, 8] also consider stress-testing to be detrimental to small business credit access. Conversely, in broad loan categories, [24] and [25] find little or no effect on credit supply using a sample covering mostly stress-tested banks. Prior to the crisis, CCAR banks were operating with historically lower capital ratios than smaller non-CCAR banks, and the implementation of the stress tests and capital requirements has resulted in CCAR banks having to raise large amounts of capital. [25] argue that the higher capital buffers implemented in the new regulatory framework to make banks more resilient have altogether put banks in a better position to lend more across some loan categories. The authors conclude that higher capital buffers have favoured the lending capacity of CCAR banks relative to other banks.

Stress tests are forward looking exercises that have been providing regulators with information about tail risks. Unlike traditional supervisory examinations that are generally kept confidential, the results of bank stress tests are frequently publicly disclosed in order to enhance transparency and promote market discipline. However, the FRB's objections or conditional approval of a capital plan can alter even a wellcapitalised bank's ability to distribute capital back to shareholders, as well as curtail plans for growth in the near-term. An interesting finding by [30] asserts that the banks that performed poorly on the stress tests tended to have dissimilar portfolios before 2011. However, after the tests showed which banks would experience high capital shortfalls under the extremely adverse scenario, these poorly performing banks altered their portfolios to more closely resemble the portfolios of banks that did do well on the tests. They argue that these shifts have resulted in an extraordinary increase in the amount of loss-absorbing capital buffers, as well as a reduction in balance sheet risk for each of the largest banks operating in the U.S. In the same context, regarding information disclosure, [29] use game-theoretical analysis in a multi-receiver framework of Bayesian persuasion to demonstrate that a banking authority can deliver superior information by optimally choosing and disclosing the stress-testing methodology and the stress test result. They suggest that regulators should not aim to completely eliminate uncertainty on the actual state of the banking sector so that the extreme forms of investor behaviours, e.g., complete withdrawal from bank financing, are not triggered.

4. Data

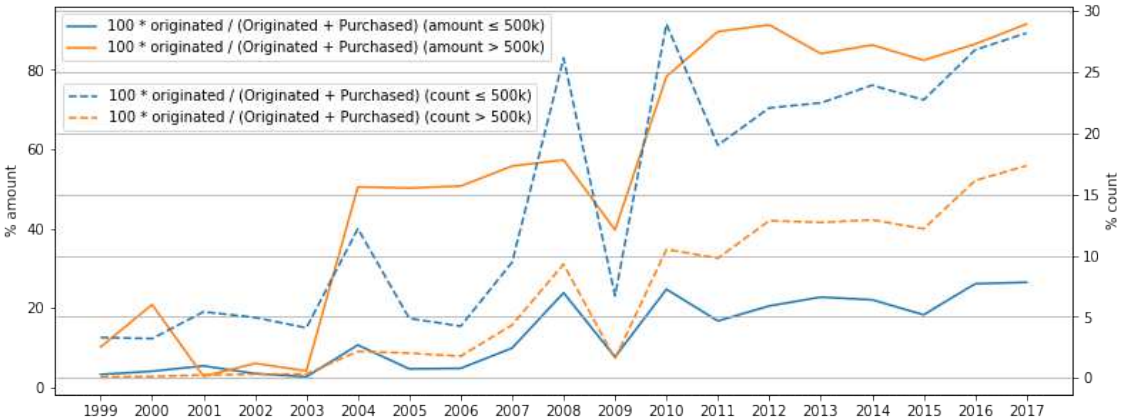
4.1. Home Mortgage Disclosure Act (HMDA)

For the purposes of our study, HMDA loan level data was used to extract originated or accepted mortgages for the years between 2000-2017. In HMDA reporting a code value, such as NA for applicant and co-applicant ethnicity, race, and sex variables mean that the loan was applied through a company rather than an individual [41, 9]. The datasets are produced annually and disaggregated at the county level for each bank. We also remove any loan-level observations that have missing, incomplete, or erroneous information on basic loan and consumer characteristics.

Purchased loans: Banks report the loans they sold to institutional investors, servicing shops or the government sponsored entities for servicing and/or securitisation. Many institutions sell their loans to institutional investors, servicing shops or to U.S. government sponsored entities (Fannie Mae, Freddie Mac, Ginnie Mae, Farmer Mac) for servicing and/or securitisation. If an institution sells all or a majority portion of their loans in the same calendar year in which the register is published, they must report to whom it was sold. If a financial institution acquires covered loans in bulk from another institution (for example, from the receiver for a failed institution), but no merger or acquisition of an institution or acquisition of a branch office is involved, the acquiring financial institution reports the covered loans as 'purchased loans.' HMDA origination records that are reported as sold to a non-government sponsored enterprise match HMDA records for loans reported as purchased (i.e., not originated by the reporting lender). This indicates significant double counting.

After extracting home equity business loans from the yearly loan application registers, we took further steps to minimise double counting. First, purchased loan entries that were sold in the year they were originated are removed. These are separately entered in the HMDA data as originated loans by originating banks. Purchased loan entries that also has a "purchaser type" code is also removed. The presence of this code indicates repeat entries as the same loan is sold to another buyer. This will retain only the loans the banks actually hold at the time of reporting.

Figure 3. Originated loans % of total (originated+purchased)



As can be observed in fig. 3., about 19.2% of total amount originated in the overall data are classified as sold in the year of origination. By definition of the appropriate HMDA code, these are not counted in the purchased loans section of the buying banks' HMDA filing. The actions reported to HMDA by the banks applicable to this study include loan originated, application approved but not accepted, application denied by financial institution, and loan (re)purchased by the institution. In the HMDA data, among all originated+accepted+purchased loans, the proportion of originated+accepted loans represent a large majority. When this sample is restricted to business loans only, the proportion is almost the opposite, that is, the purchasing activity among business loans is much higher. In our analysis we use samples with and without purchased loans. Regression outputs (section 6) show different results.

4.2. FDIC (Federal Deposit Insurance Corporation)

The FDIC statistics on depository institutions provide comprehensive financial and demographic data for all FDIC-insured institution. All the control variables used in this study are obtained from FDIC except county/state populations which are obtained from the U.S. census bureau.

5. Demand for home equity business loans

As we can see in fig 3, home equity business loan counts show some structural change in its trend just after the crisis across all groups. However, fig 4, does not indicate whether post-crisis regulations and stress testing have adversely affected it at aggregate level. In fact, after the initial fall in 2007 and 2008, it has grown steadily over the years. A noteworthy point here is that, in the business finance category of home equity loans, purchased loans made up a much higher proportion of total busines loans compared to all loan originations until 2009. Purchased loans do not add more credit to the economy directly as the number of total loans remains the same. However, they help free up resources of the loan selling banks, thereby allowing them to give away other categories of loans.

During the 2000s and the American housing bubble, initial low interest rates allowed homeowners to borrow cheaply, but in the years after 2008, higher interest rates meant borrowers were no longer able to use HE loans/credits with the same ease. All else being equal, interest rates alone would have dampened home equity business financing. Nevertheless, HE business loans remain largely unaffected on the aggregate level compared to home purchase loans; this could be because HE loans were less exposed to subprime borrowing. However, in fig 4 and 5 we can see that since 2004 loans larger than $1.5m comprise more than all the others combined; and yet loans in this size category account for little over 8% of the applications while loans under $0.5m account for 75% of all applications. 2003-04 is also the only year in the whole study period where the total mortgage volumes (i.e., across all categories and including home equity loans) have surpassed $3 trillion. In the HE business finance subset, the trend is more or less proportionate, as can be seen in figs 4 and 5

Figure 4. Originated HE business loans amounts (log) - various sizes

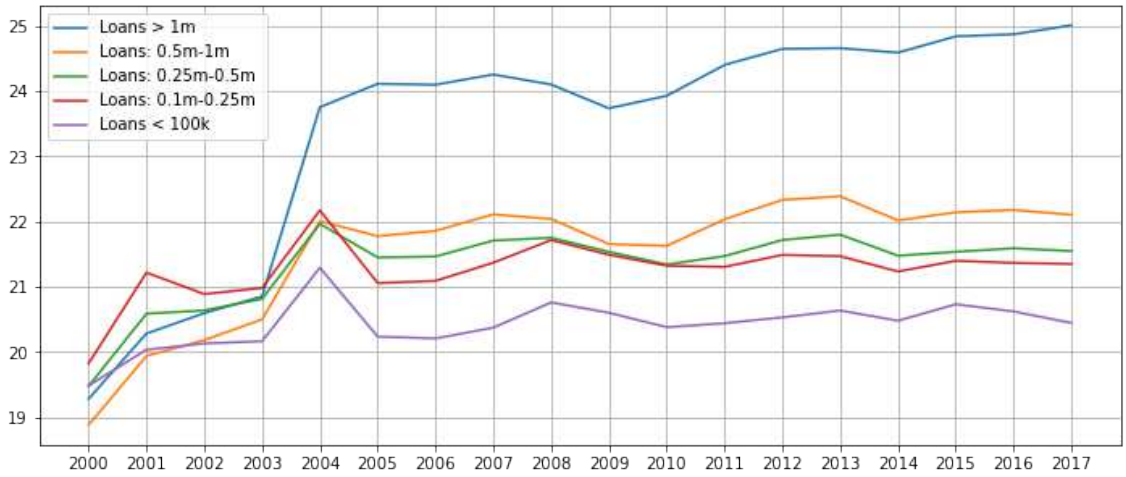


Figure 5. Originated HE business loans count

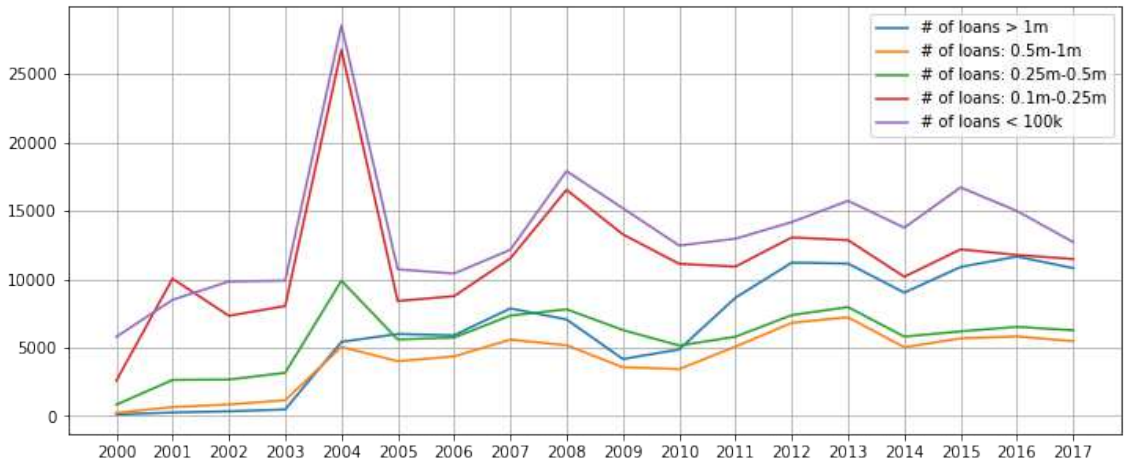
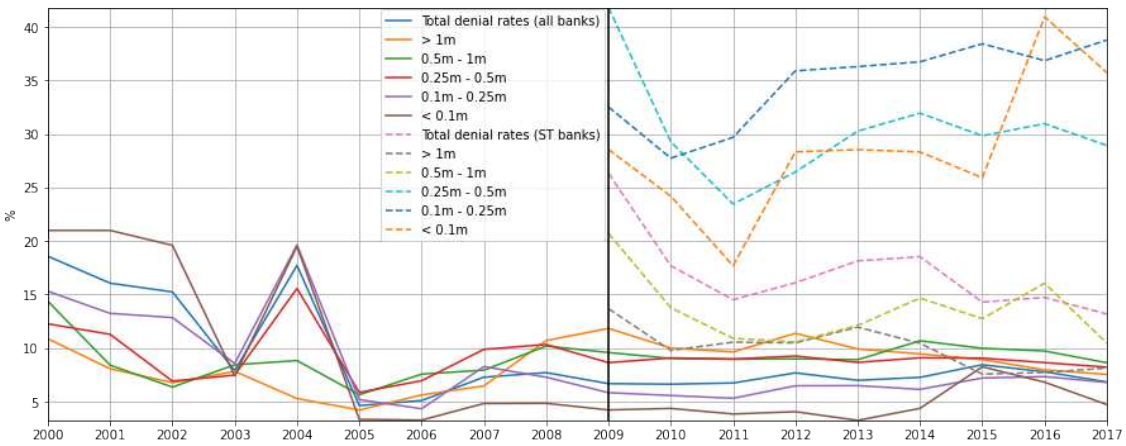


Figure 6. Loan denial rates



In figs 7 and 8, we can see that loan originations larger than $1m make up a small proportion of all applications, but have been increasing over the years. However, the distributions also show that the frequency of smaller sized loans are decreasing years before the crisis and the enaction of regulatory testing. Distributions in figs 9 and 10 show strong contrast in loan size distribution between stress tested and non stress tested banks. Vast majority of loans originations from non stress tested banks are under 0.5m while stress tested banks have more even distributions of small and large loans amounts. Both have originated fewer loans smaller than 0.25m and increased loans of size 0.5m and above.

In terms of loan purchases, there is a divergent pattern between stress tested and nonstress tested banks. There exists a thriving secondary market for loans because banks have been selling loans for many decades, either outright, through participation and syndications, or through securitisation. Several reasons for asset sales are mentioned in [42]. Asset sales may allow a bank to avoid "regulatory taxes", i.e., reserve requirements, capital requirements, and deposit insurance premiums. Also, asset sales may facilitate gap management and enhance a bank's liquidity and diversification.

Between 1980 and 2008 the value of home equity loans outstanding increased from $1bn to $1tn with ownership by almost a quarter of homeowners being a first mortgage. It was a highly lucrative business for banks; their returns on fixed-rate home equity loans and lines of credit were 25-50% higher than returns on consumer loans overall, with much of that premium coming from relatively high fees [5].

Home equity business loans however has been a small subset of total outstanding. Fig 4 shows the total amount of HE business loans originated each year from 1999-2017. Their rate of growth is roughly porportional to the overall growth in all HE loans. The solid lines in fig 3 represent the proportion of originated loans to total holdings of HE business loans (originated / (originated + purchased)). Purchased loans were reported even if they were sold by the institution, e.g., if a failed bank was acquired by another bank without a merger or acquisition, or if a certain bank originated a loan and sold it to another in a given year, but bought the loan back in the next year. The first bank will report it as origination. They will also report the purchaser type code in the same year; this, however, is not a part of our data. If the bank purchased this loan in a different reporting year, it will be listed as purchased loan.

[5] https://www.nytimes.com/2008/08/15/business/worldbusiness/15iht-sell.4.15338803.html

Figure 7. Loan origination size distribution (All banks)

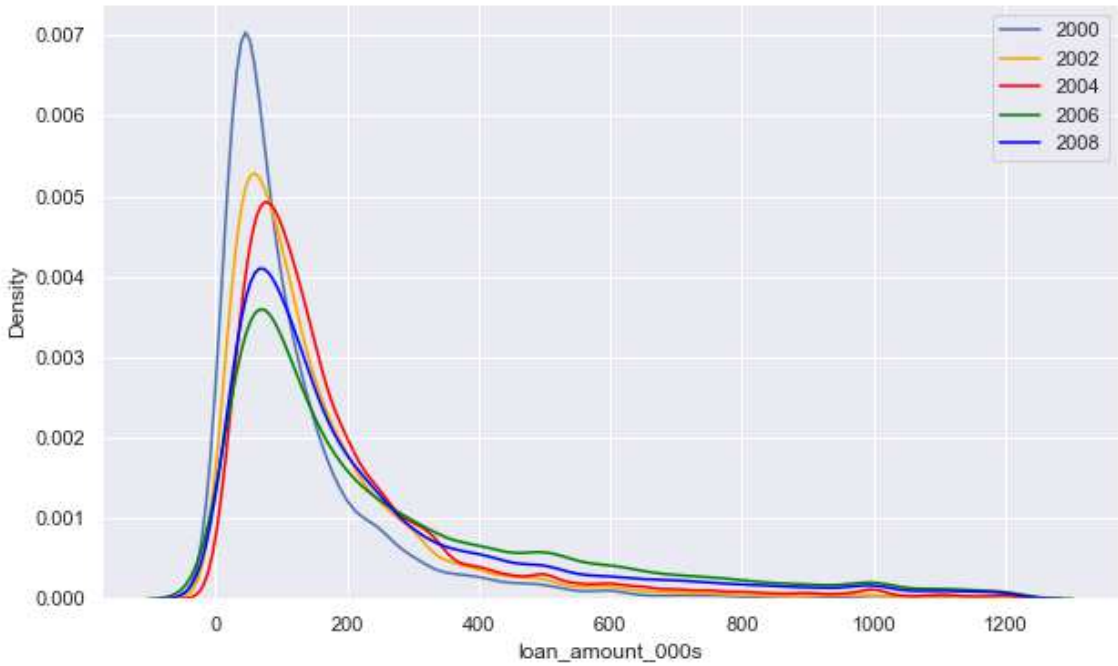


Figure 8. Loan size origination distribution cumulative (All banks)

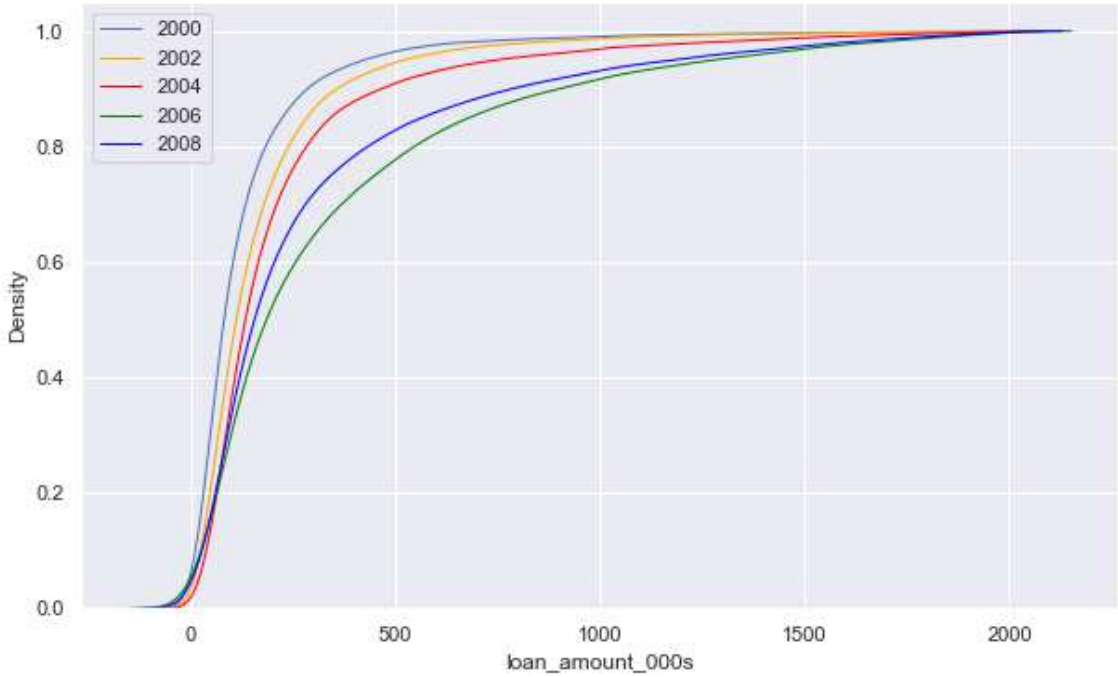


Figure 9. Loan size origination distribution (Stress tested banks)

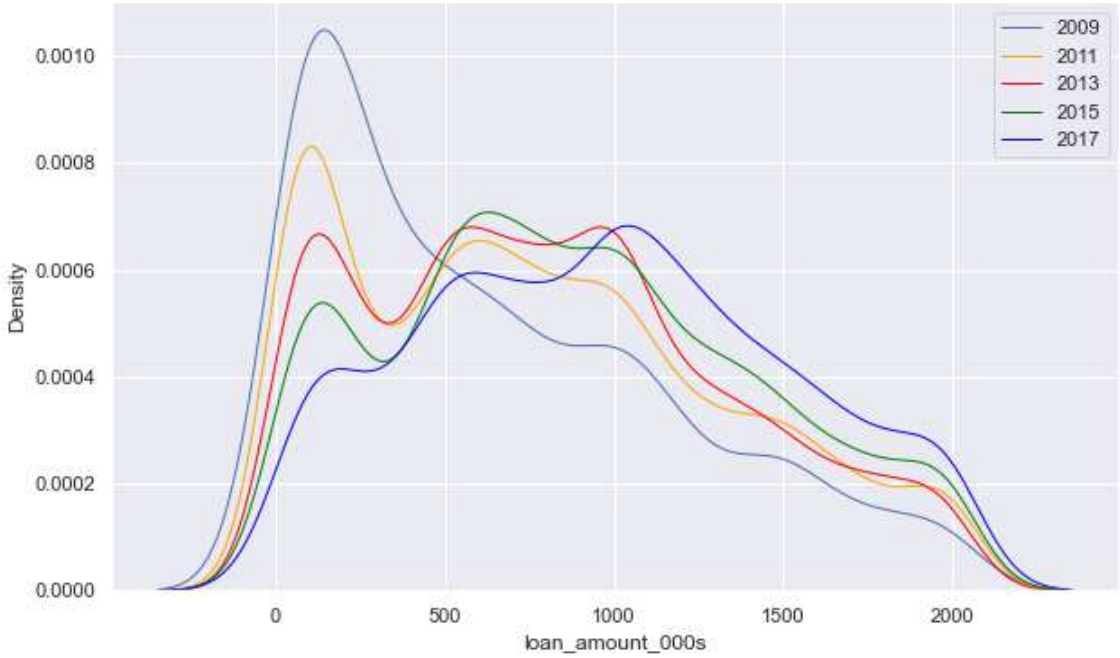


Figure 10. Loan size origination distribution (Non stress tested banks)

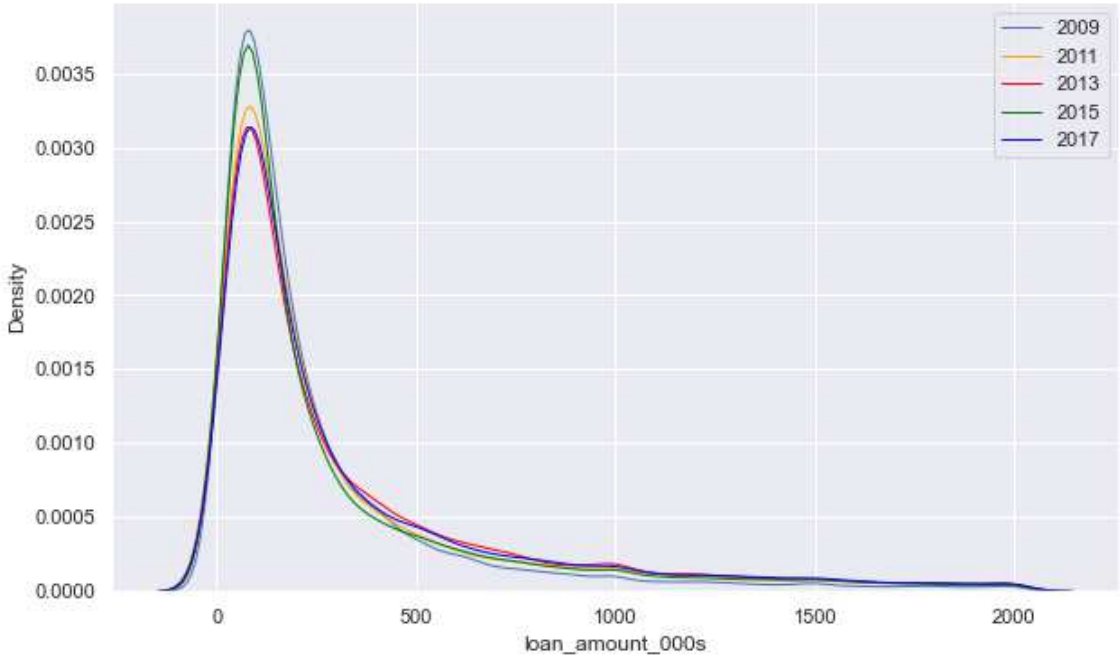


Figure 11. Loans amt % change (All banks) $<$ 100k (2011/2 - 2016/7)

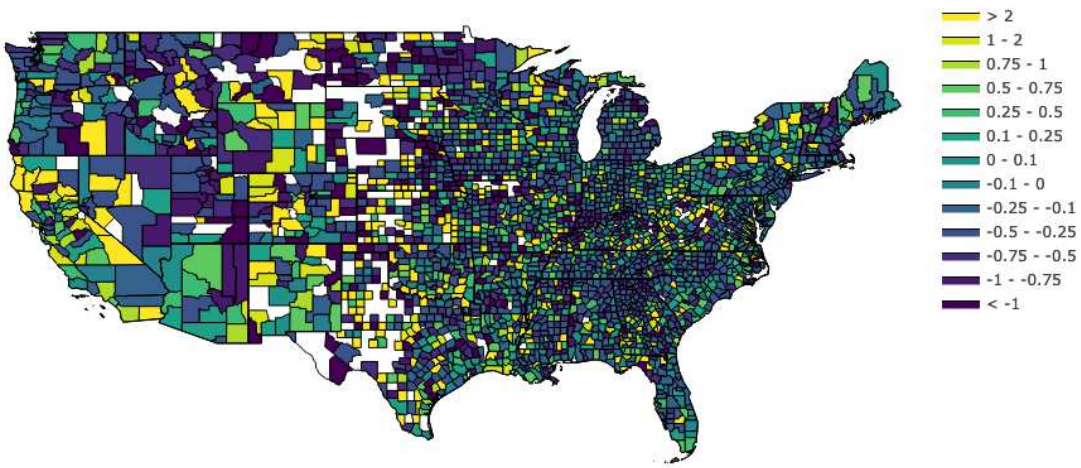


Figure 12. Loan amt % change (Non-stress tested banks) $<$ 100k (2011/2 - 2016/7)

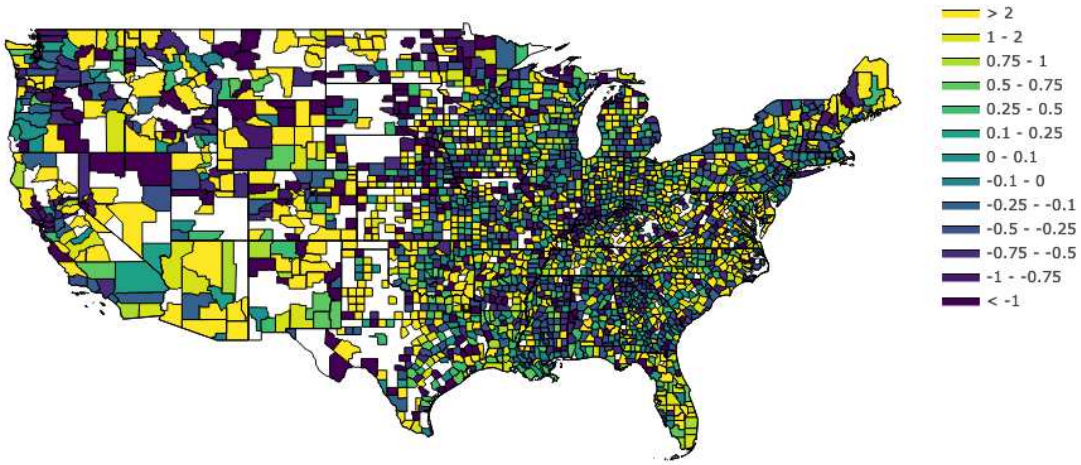


Figure 13. Loan amt % change (Stress tested banks) $<$ 100k (2011/2 - 2016/7)

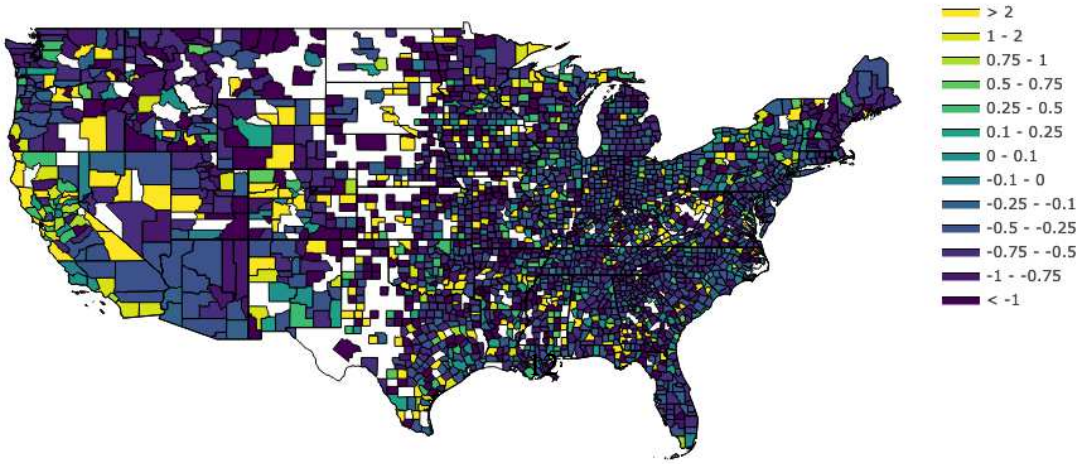


Figure 14. Loans amt % change (All banks) 100k-250k (2011/2 - 2016/7)

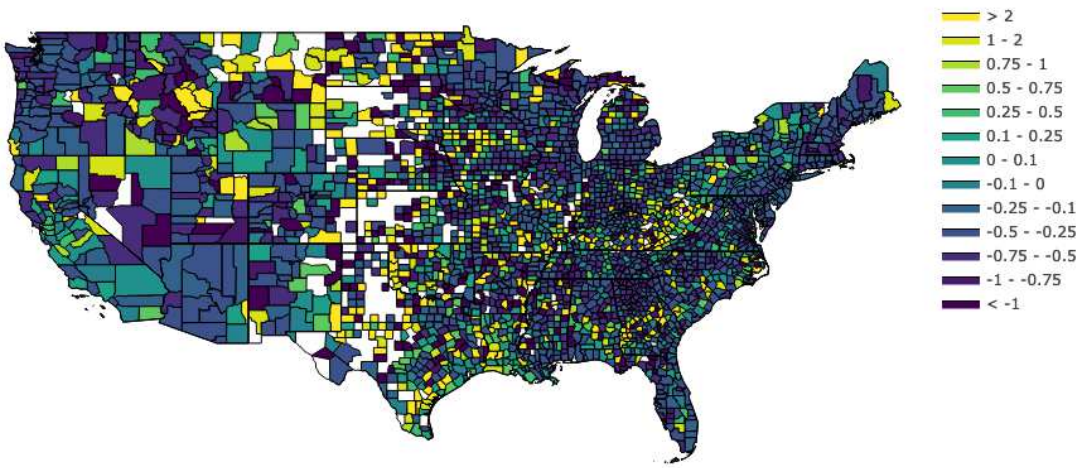


Figure 15. Loan amt % change (Non-stress tested banks) 100k-250k (2011/2 - 2016/7)

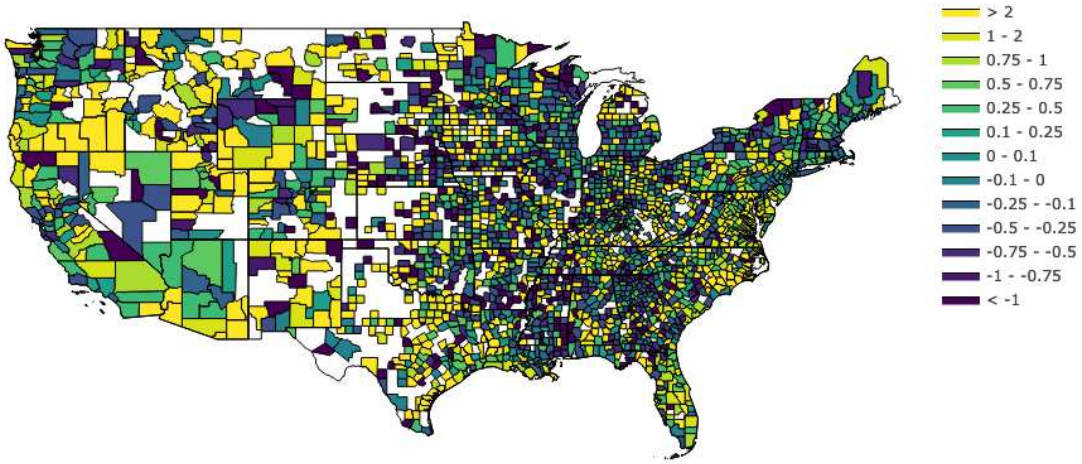


Figure 16. Loan amt % change (Stress tested banks) 100k-250k (2011/2 - 2016/7)

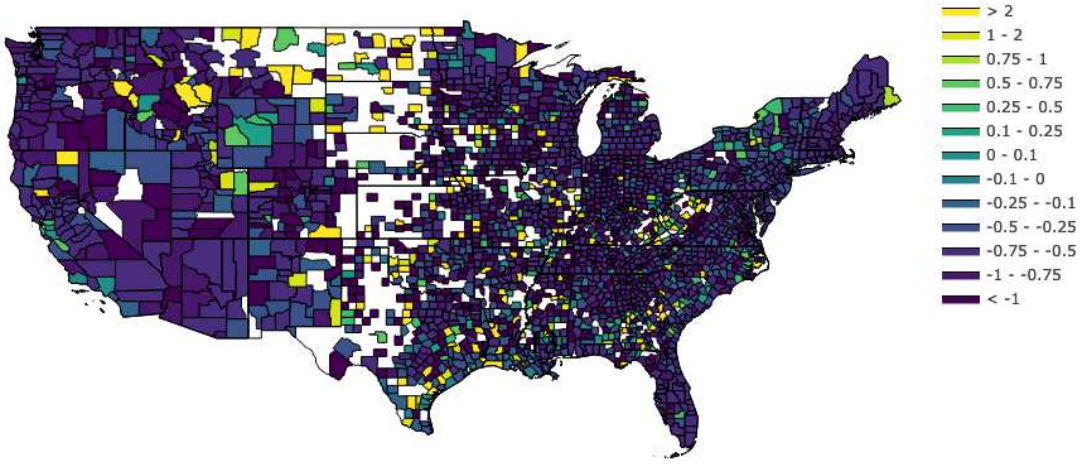


Figure 17. Loan amts % change (All banks) 250k-500k (2011/2 - 2016/7)

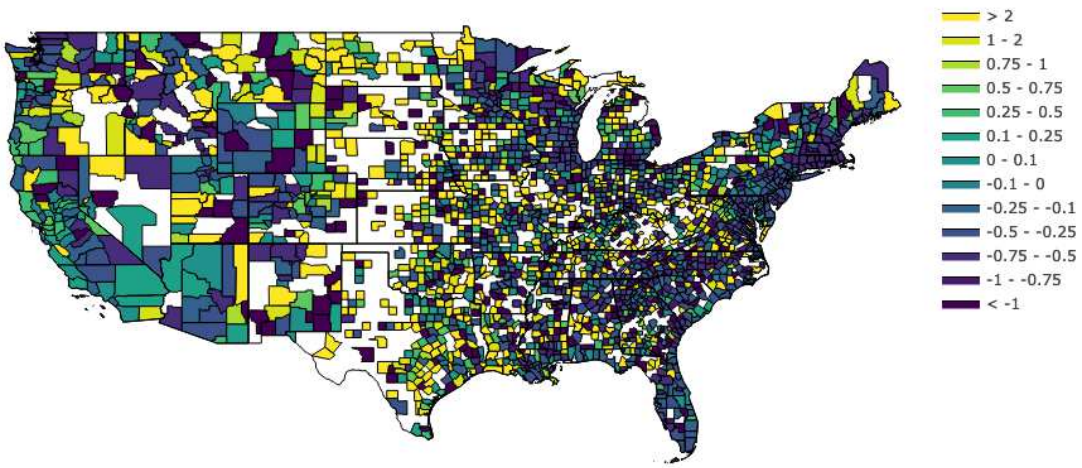


Figure 18. Loan amt % change (Non-stress tested banks) $<$ 250k-500k (2011/2 - 2016/7)

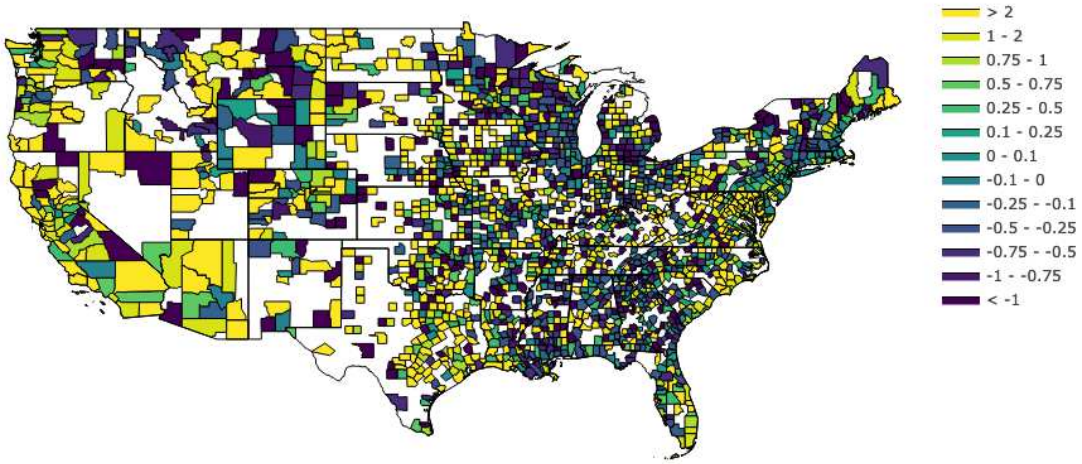


Figure 19. Loan amt % change (Stress tested banks) $<$ 250k-500k (2011/2 - 2016/7)

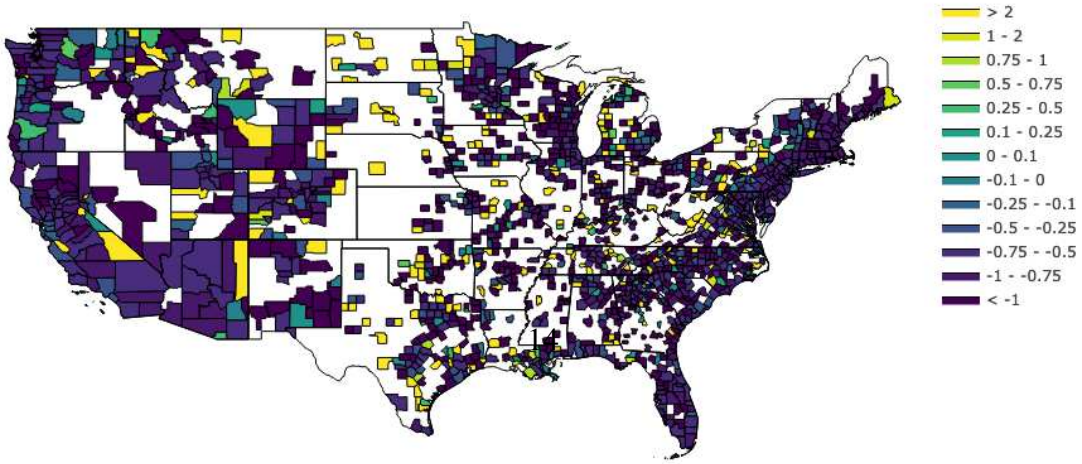


Figure 20. Loans amt % change (All banks) 500k-1.5m (2011/2 - 2016/7)

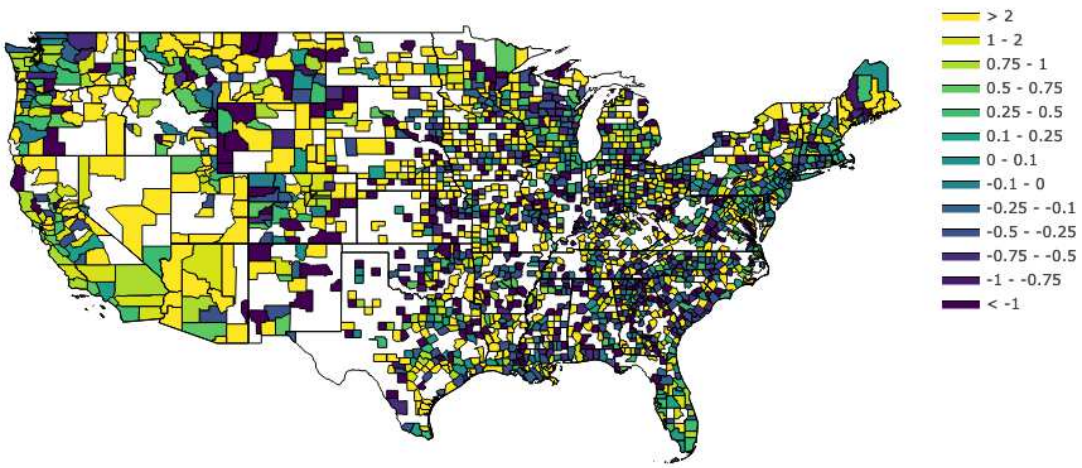


Figure 21. Loan amt % change (Non-stress tested banks) < 500k-1m (2011/2 - 2016/7)

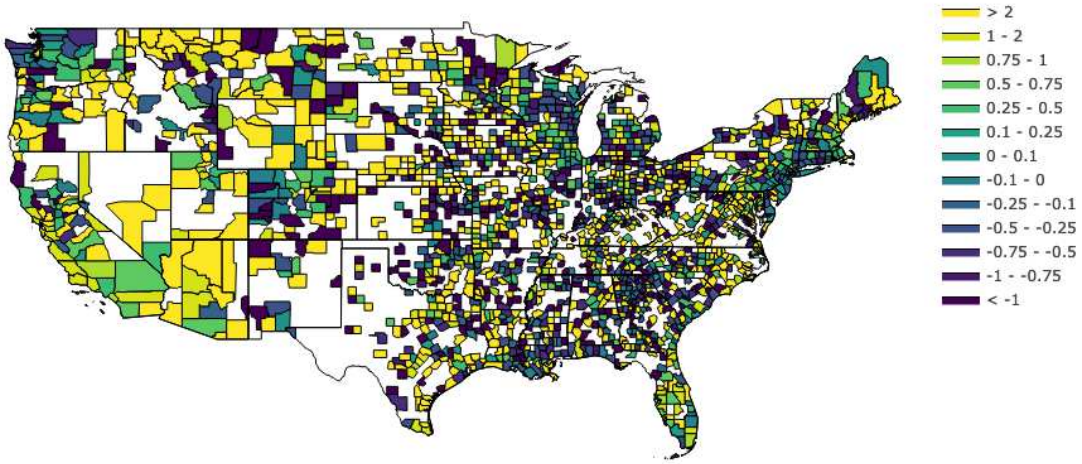


Figure 22. Loan amt % change (Stress tested banks) < 500k-1m (2011/2 - 2016/7)

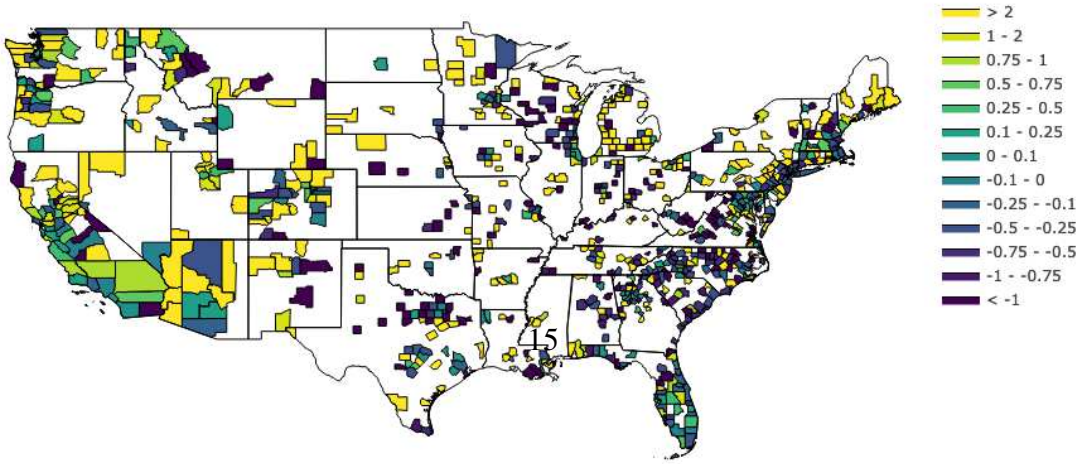


Figure 23. Loans amt % change (All banks) 1.5m+ (2011/2 - 2016/7)

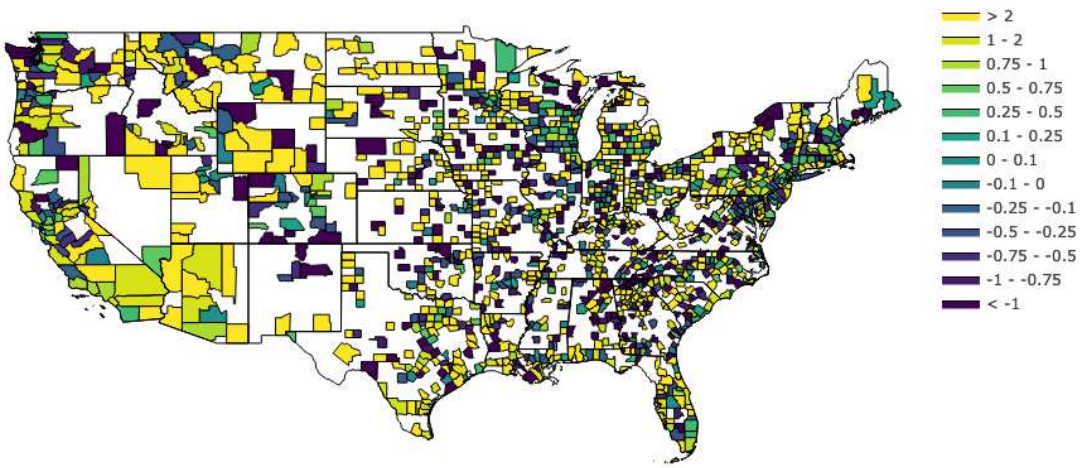


Figure 24. Loan amt % change (Non-stress tested banks) < 1.5m+ (2011/2 - 2016/7)

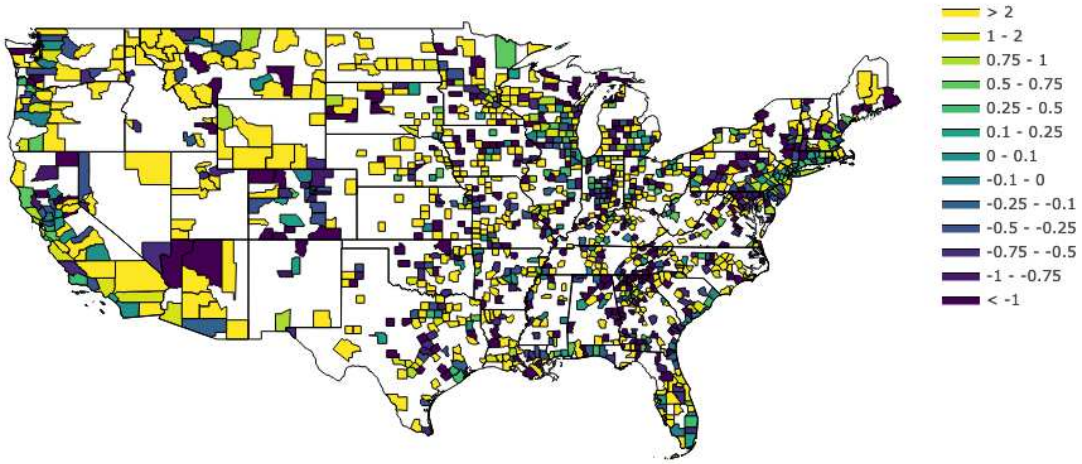
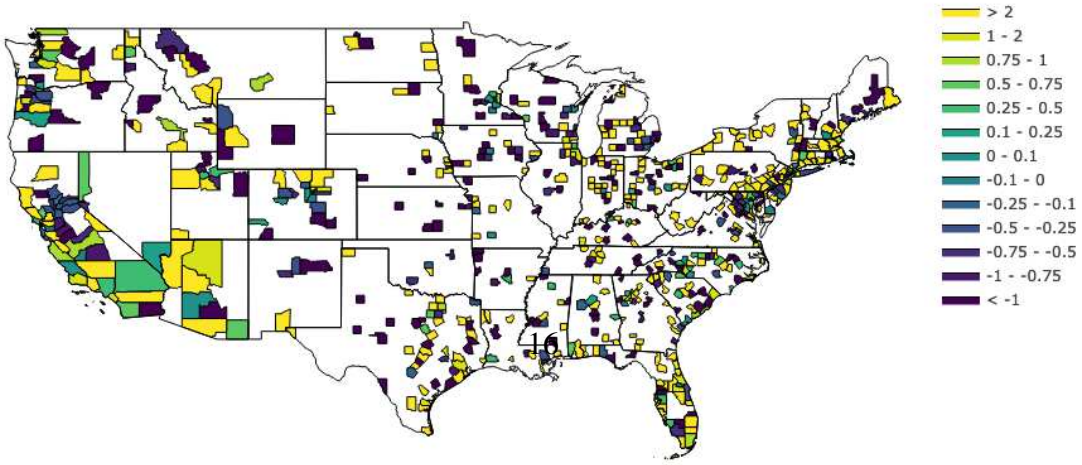


Figure 25. Loan amt % change (Stress tested banks) < 1.5m+ (2011/2 - 2016/7)



Figs 11 - 25 depict the choropleth plots of percentage changes in loan amounts from 2011/2 to 2016/7. Three plots from each loan size category correspond to the total originations in the U.S., originations by ST banks, and originations by non-ST banks. The difference between the ST and non-ST banks are visually evident across all loan size categories. In the next section, we describe our methodology for studying the nature of these differences in five loan sizes and three categories of banks (e.g., banks that passed the test, banks that failed the test, and banks that did not go through the test).

6. Empirical models and results

We run several fixed effects regression models to determine shift in lending behaviour in home equity business loans. Each model is tested for different size categories on both loan originations and purchased loans. At bank-year-county and bank-year-state levels, we assess how stress tested banks and those with poor stress test results change their home equity lending portfolio. For county level models, another set of analyses is done bank-county and county-year interactions. Controls include total assets; ratio of multifamily dwellings investments to total loans; total charge-offs; return on assets; ratio of securitisation activities of principal balance for home equity lines to total debt securities; and population. Two dummy variables included in the model are (a) BHC of the respondent adequate in the stress test, and (b) BHC of the respondent, had its plans objected or failed a stress test. In county level analysis, the output variable (amount) includes loans that are originated and approved but not accepted. The loans that were approved but not accepted constitute a negligible proportion compared to originated loans, and its inclusion does not change the regression outputs. We use robust standard errors on the county level regressions (to obtain unbiased standard errors of OLS coefficients under heteroscedasticity). In the state level fixed effects models, we cluster coefficients at the county level.

$$log(amt_{Originated})_{b,c,t} = \gamma_1 \, \mathbf{S}_{b,t} + \gamma_2 \, \mathbf{O}_{b,t} + \text{FE}_{b,c} + \text{FE}_t \tag{1}$$

$$log(amt_{Purchased})_{b,c,t} = \gamma_1 \, \mathbf{S}_{b,t} + \gamma_2 \, \mathbf{O}_{b,t} + \text{FE}_{b,c} + \text{FE}_t \tag{2}$$

$$log(amt_{O \cup P})_{b,s,t} = \gamma_1 \, \mathbf{S}_{b,t} + \gamma_2 \, \mathbf{O}_{b,t} + \text{FE}_{b,s} + \text{FE}_t \tag{3}$$

log(amt) refers to log amount of home equity loans to businesses by bank b in county c (or state s) in year t. $S_{b,t}$ is a dummy variable with a value of one for each year a bank undergoes stress tests, and zero otherwise. It is useful to breakdown the loan amounts into size categories given that loans $\leq$.25m account for 62% (71%) and loans of size .25m-1m account for 28% (24%)of the loans for non ST banks in 2017 (2009).The distributional difference between ST and non-ST banks lending is noteworthy. Negative coefficients with high effect sizes on smaller sized loans on the pass/fail dummy variables do not necessarily mean large movements in their portfolios or even in market supply of credit. ST banks have less than 12% (32%)of their lending that is $\leq$.25m in 2017 (2009). For 0.25m-1m, this is 43% (43%).

Table 1. HE business loan origination amount (000s) percentiles

		50%	75%	90%	98%
ST banks	**2009**	513	1000	1500	1925
	2013	760	1155	1600	1959
	2017	1000	1370	1743	2000
Non-ST banks	**2009**	138	299	631	1500
	2013	167	431	933	1684
	2017	164	421	933	1680

Our regression analysis results on bank-county-year level, with and without interactions, are similar in direction, but different in magnitude of the pass/fail dummy variable coefficients. Results at state level, combining both originated and purchased loans, are also reported. In table 3 we can see that the state level coefficients have a slightly stronger magnitude than expected, given the results for county level models. One reason for this finding could be because stress tested banks have withdrawn from several counties and have concentrated their investment in fewer counties within a given state. Another reason for the difference in errors could be that many banks, especially those that are smaller, tend to have their lending concentrated in fewer locations with fewer than two, and many with no originations in most counties. There is also significant disparity in lending activities between counties and types of banks. The difference, however, can reveal insights into the underlying noise in observations. The advantage of county level analysis is that it has more granular coverage and picks up signals from activities from subsidiaries and branches of banks to identify a pattern, but also suffers from smaller amounts of data in each geographical subset. Conversely, state level data provides more data points, and hence better signals for each geographical subset despite the reduction in geographical granularity. In short, the state level analysis may provide smaller errors while county level date provides better inferences.

Figure 26. Regression coefficients for CCAR stress test dummy variables (pass/fail)
Year, bank, and county/state fixed effects

	County		State
	Originated	**Purchased**	**All HEBLs**
<0.1m	-.24 / -.34	-.30 / -.84	-.48 / -.99
0.1m - .25m	-.18 / -.21	.13 / -.23	.03 / -.31
.25m - 0.5m	*-.02* / -.06	*.09* / -.30	*.01* / -.32
.5m - 1.5m	*.02* / *.04*	.03 / -.42	-.04 / -.26

- HEBL: All home equity business loans include originated and purchased loans that were not (re)sold in the reporting year
- Originated loans also include those that were sold in the reporting year
- The first coefficient represents dummy variables assigned to the banks that passed the CCAR stress test exercise and the latter represents those that failed the exercise
- Italicized estimates are not significant at 1% or 5% alpha level

Table 2. Regression coefficients for CCAR stress test dummy variables (pass/fail) Bank-county, and year-county interaction effects

	County	
	Originated	**Purchased**
<0.1m	-.39 / -.50	-.32 / -.92
0.1m - .25m	-.38 / -.43	.11 / -.44
.25m - 0.5m	-*.07* / -.17	.08 / -.49
.5m - 1.5m	.11/ .12	*.06* / -.79

- Originated loans also include those that were sold in the reporting year
- The first coefficient represents dummy variables assigned to the banks that passed the CCAR stress test exercise and the latter represents those that failed the exercise
- Italicized estimates are not significant at 1% or 5% alpha level

Detailed regression outputs are listed in Appendix 1. First, we note that for originated & purchased loans under 0.25m, our sample has 632,824 observations (figs 19 and 21), while 0.25m-1.5m has 261,217 samples (21 and 25).

This distributional difference are also observed in figs [7 8 9 10]. In 2017, loans under 1m represented less than 91% of total originations for non-ST banks compared to only 54% for their ST counterparts. In both categories of banks, the amounts under the same percentiles have increased since 2009, where the loans amounts were under 0.7m for non-ST banks and 0.685m for ST banks. Results show that ST banks have decreased their loan originations under 0.25m, but do not show evidence to support differences in loan originations above 0.25m compared to non-ST banks. In the results for purchased loans, the failed banks have coefficients between -0.23 and -0.84. Failed banks decreased their purchase of loans under 0.1m by 84% compared to other banks. There is a divergent pattern between passed, failed, and non-ST banks, either in magnitude or direction. Failed banks decreased their loan purchase activities across all categories of loan sizes while passed banks increased loan purchases of loans larger than 0.1m compared to nonST banks.

In county level regression analyses of loans between 0.5m-1.5m, the dummy coefficients for both passed and failed banks are not statistically significant, indicating insufficient evidence to verify that ST banks (that pass or fail the stress test) reduce their originations of small business lending compared to non-ST banks. This is also the case for pass dummy coefficient in regression for originated loan category between 0.25m-0.5m and purchased loan category between 0.5m-1.5m. Finally, in the state level regression of loan category between 0.25m-0.5m, the coefficient of "pass" dummy is not significant. The insignificant estimates are italicised in table 6 In all other regression runs, the dummy variable coefficient estimates are statistically significant at 1% or 5% alpha level.

However, another subset of data for analysing the impact of stress test to banks holdings of HE loans are those that include both originated and purchased loans [6]

In loan size categories under $0.25m, state level results show stronger effect sizes com-

[6]As mentioned above, when processing the data, all loans that were purchased by a given bank which were also marked as sold were excluded from the originated loans. This ensures that at the time of reporting for the year, the loans included in data are the loans each banks held as their assets. This is particularly important as often when a non defaulting bank Bank A sells loans to Bank B, Bank A is able to lend to other borrowers, and essentially Bank B is adding to its portfolio of investments in loans.

pared to county level dummy variables although the direction of the coefficients is the same. One possible reason for this could be temporal and spatial heterogeneity in loan distribution, e.g., Bank A provides $10m in loans in county A and $0 in county B in year 1, and $0m in county A and $10 in county B in year 2. If both counties are located in the same state, then in either year the state will have $10m from bank A. Such geotemporal differences will impact the fixed effects intercepts in state and county as the county version is more likely to be affected by errors because it is much more likely for a bank to withdraw from supplying loans to a particular county rather than a state. A second reason for such differences in state-county effect sizes could be due to acquisitions and/or bank failures. If a non-ST bank operating in only one county fails, then in county level regression it will affect only one county intercept out of over 2000. In state level regression it will affect one state intercept out of 50. However, the impact to the county intercept will be stronger compared to the impact to the state level intercept. This is due to the likelihood that the average relative market coverage of a bank will be higher in its operating county rather than in its operating state. Third, it is also possible that ST banks have increased their loan originations in areas where they already had high exposure, and have also reduced their geographical diversification. Alternatively, it could be that non-ST banks had increased their presence in new locations.

County level results show that passed and failed ST banks have decreased lending of loans ¡ 0.1m by 22% and 28%, respectively, compared to non-ST banks. However, in the remainder of the loan breakdowns categories, ST banks have increased their originations. Under purchased loans, in both 0.25m and all loans category, the failed dummy coefficient is approximately -0.5 under state and county. But differ strongly but consistently all categories on passed dummy. The coefficients for county level are -0.5 and 0.5, and for state level are 0.45 and 0.43, which can be interpreted either as an decrease in geographical coverage and concentration in specific areas in part of ST banks, or it could also be that non-ST banks have decreased their loan purchases.

7. Conclusion

Several studies used the peak of the 2000s' housing bubble as a reference for comparing the credit supply in subsequent years in the U.S. Such an approach can be unreliable as it implicitly assumes that this peak is desirable; whereas in reality, the high credit supply was an outcome of an overdriven economy with systemic risk repercussions extending to the wider economy. In the choropleths in section 4 (figs 11 - 25), we used a reference point three years after the crisis (when the impact of the recession had begun to subside) in order to visually identify the geographical changes in loan originations.

Credit risk is possibly the dimension of risk with the biggest bank regulation regarding stress tests. Hence, it has significant effects on capital adequacy. This has negatively affected credit supply which can prevent small firms and startups from manifesting innovative ideas or taking growth opportunities. We found evidence that ST banks that both passed and failed the CCAR exercise have decreased their originations of HE business loans under 0.25m compared to non-ST banks by over 38% and 43% respectively. The amount that is most frequently sought by small firms.

Failed banks have also decreased their loan purchases by a significant proportion com-

pared to other non-ST banks. The difference is stronger when compared with passed banks, given that they have actually increased their purchases of loans over 0.1m. This may be part of a strategic response for avoiding the reserve requirements, capital requirements, and deposit insurance premiums. The banks that had conditional objection in their CCAR results may also have had decreased purchases aimed to facilitate the gap management and enhance their liquidity and diversification.

Understanding how banks or markets react to regulatory testing is key to the management of spillovers and systemic risk. Our results can be useful in the design and deployment of stress tests as the driving forces behind bank decisions regarding loan origination, purchase and sales are important for the regulation. Regulators should concentrate on both asset composition and asset quality by risk-adjusting capital requirements [42]. E.g. If banks are reducing high quality loans from their books in response to stringent stress testing, then some hurdles should be lowered. If, however, loan sales are primarily influenced by other factors such as liquidity and diversification, then loan sales should be encouraged. Given the extent to which the failed banks have reduced their loan purchases, it is likely that they have reduced both high- and low- quality loans. However, this could be verified in a further study, since understanding the steps banks make, or knowing if there exists a common standard procedure that banks employ to stay within regulatory barriers when they receive a conditional approval in the exercise, could aid in optimising welfare from regulation.

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Appendix

7.1. Regression results

7.1.1. Bank county level (origjnated)

Table 3. Loan size $\leq$ 0.1m

```
HDFE Linear regression                            Number of obs   =     88,202
Absorbing 3 HDFE groups                           F(   9,  80874) =      22.42
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.2742
                                                  Adj R-squared   =     0.2084
                                                  Within R-sq.    =     0.0025
                                                  Root MSE        =     0.7985
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.0468204	.0135529	3.45	0.001	.0202569	.0733839
real2loans	.1010227	.0136207	7.42	0.000	.0743262	.1277192
drlnlsq	-.0061316	.0025791	-2.38	0.017	-.0111867	-.0010765
roaq	.0195114	.0102938	1.90	0.058	-.0006643	.0396871
hesecr	-.0030868	.0029481	-1.05	0.295	-.008865	.0026915
nonincr	-.3065216	.0715992	-4.28	0.000	-.4468556	-.1661876
population	-.1122206	.2631222	-0.43	0.670	-.6279384	.4034973
adequate	-.2424405	.0259623	-9.34	0.000	-.2933265	-.1915545
objection	-.3453099	.0473299	-7.30	0.000	-.4380761	-.2525437
_cons	11.22533	.6895992	16.28	0.000	9.873723	12.57694

Table 4. Loan size $\leq$ 0.1m

```
HDFE Linear regression                            Number of obs   =     52,056
Absorbing 2 HDFE groups                           F(   8,  29777) =      18.81
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.6132
                                                  Adj R-squared   =     0.3238
                                                  Within R-sq.    =     0.0061
                                                  Root MSE        =     0.7690
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.1101157	.0241892	4.55	0.000	.0627038	.1575275
real2loans	.1764342	.024609	7.17	0.000	.1281995	.2246689
drlnlsq	-.0082325	.0039704	-2.07	0.038	-.0160147	-.0004504
roaq	.0318014	.0170232	1.87	0.062	-.0015649	.0651676
hesecr	.0030059	.0053103	0.57	0.571	-.0074025	.0134143
nonincr	-.2428064	.1293633	-1.88	0.061	-.4963641	.0107513
adequate	-.3964016	.0494051	-8.02	0.000	-.4932378	-.2995654
objection	-.5068642	.0827336	-6.13	0.000	-.6690256	-.3447028
_cons	10.41545	.319943	32.55	0.000	9.788349	11.04255

Includes bank-county and year-county interaction effects

Table 5. Loan size 0.1m $<$ X $\leq$ 0.25m

HDFE Linear regression
Absorbing 3 HDFE groups

Number of obs	=	85,544
F(9, 78185)	=	29.84
Prob > F	=	0.0000
R-squared	=	0.2484
Adj R-squared	=	0.1777
Within R-sq.	=	0.0032
Root MSE	=	0.6493

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.0845017	.0107342	7.87	0.000	.0634626	.1055407
real2loans	.0694711	.0095991	7.24	0.000	.050657	.0882853
drlnlsq	-.0070346	.0019406	-3.62	0.000	-.0108382	-.003231
roaq	-.0027799	.0077995	-0.36	0.722	-.0180669	.0125072
hesecr	.0127576	.002184	5.84	0.000	.0084769	.0170383
nonincr	-.1805252	.0539039	-3.35	0.001	-.2861765	-.0748739
population	-.0044998	.6811628	-0.01	0.995	-1.339575	1.330576
adequate	-.1816863	.018784	-9.67	0.000	-.2185028	-.1448698
objection	-.2132659	.0297737	-7.16	0.000	-.2716221	-.1549096
_cons	11.52693	1.741093	6.62	0.000	8.114401	14.93947

Table 6. Loan size 0.1m $<$ X $\leq$ 0.25m

HDFE Linear regression
Absorbing 2 HDFE groups

Number of obs	=	51,676
F(8, 29564)	=	26.06
Prob > F	=	0.0000
R-squared	=	0.6001
Adj R-squared	=	0.3011
Within R-sq.	=	0.0094
Root MSE	=	0.6373

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.1232001	.0203051	6.07	0.000	.0834012	.1629989
real2loans	.1380773	.0185748	7.43	0.000	.10167	.1744847
drlnlsq	-.0019188	.0031551	-0.61	0.543	-.0081029	.0042654
roaq	-.0064544	.013039	-0.50	0.621	-.0320113	.0191025
hesecr	.0181573	.0042849	4.24	0.000	.0097587	.0265558
nonincr	-.0938254	.0940126	-1.00	0.318	-.2780943	.0904436
adequate	-.3861243	.0385166	-10.02	0.000	-.4616184	-.3106301
objection	-.4364708	.0608252	-7.18	0.000	-.5556909	-.3172507
_cons	11.22697	.2730944	41.11	0.000	10.69169	11.76225

Includes bank-county and year-county interaction effects

Table 7. Loan size 0.25m $<$ X $\leq$ 0.5m

HDFE Linear regression
Absorbing 3 HDFE groups

Number of obs	=	51,275
F(9, 45046)	=	3.90
Prob > F	=	0.0001
R-squared	=	0.3146
Adj R-squared	=	0.2198
Within R-sq.	=	0.0008
Root MSE	=	0.5376

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.0435445	.0109822	3.97	0.000	.0220193	.0650698
real2loans	.027136	.0091196	2.98	0.003	.0092615	.0450105
drlnlsq	-.004427	.0020193	-2.19	0.028	-.0083849	-.0004691
roaq	.0082065	.0083385	0.98	0.325	-.0081372	.0245501
hesecr	-.0009142	.0025662	-0.36	0.722	-.0059441	.0041157
nonincr	-.0803903	.0589285	-1.36	0.173	-.1958912	.0351105
population	.6746416	.7933209	0.85	0.395	-.8802806	2.229564
adequate	-.0203146	.0197228	-1.03	0.303	-.0589716	.0183424
objection	-.0642367	.0319639	-2.01	0.044	-.1268865	-.0015869
_cons	10.7543	2.046209	5.26	0.000	6.743695	14.7649

Table 8. Loan size 0.25m $<$ X $\leq$ 0.5m

HDFE Linear regression
Absorbing 2 HDFE groups

Number of obs	=	85,478
F(8, 57131)	=	306.03
Prob > F	=	0.0000
R-squared	=	0.6315
Adj R-squared	=	0.4487
Within R-sq.	=	0.0514
Root MSE	=	0.9123

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.4244004	.0175179	24.23	0.000	.3900652	.4587355
real2loans	.4315862	.0126044	34.24	0.000	.4068816	.4562909
drlnlsq	-.0288598	.0048414	-5.96	0.000	-.0383489	-.0193706
roaq	.226501	.0156844	14.44	0.000	.1957596	.2572425
hesecr	.0121244	.0017656	6.87	0.000	.0086638	.015585
nonincr	-.7841234	.091386	-8.58	0.000	-.9632404	-.6050063
adequate	.0874663	.0329448	2.65	0.008	.0228944	.1520382
objection	-.4936621	.0350266	-14.09	0.000	-.5623144	-.4250098
_cons	6.907764	.3018043	22.89	0.000	6.316226	7.499303

Includes bank-county and year-county interaction effects

Table 9. Loan size 0.5m $<$ X $\leq$ 1.5m

HDFE Linear regression
Absorbing 3 HDFE groups

Number of obs	= 47,859
F(9, 42072)	= 10.94
Prob > F	= 0.0000
R-squared	= 0.3652
Adj R-squared	= 0.2778
Within R-sq.	= 0.0025
Root MSE	= 0.5946

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.0562357	.0131226	4.29	0.000	.030515	.0819563
real2loans	-.0264579	.0091502	-2.89	0.004	-.0443924	-.0085233
drlnlsq	-.0015159	.0022573	-0.67	0.502	-.0059404	.0029085
roaq	.0506061	.0095976	5.27	0.000	.0317947	.0694175
hesecr	-.0102123	.0027445	-3.72	0.000	-.0155916	-.004833
nonincr	-.0966709	.0630023	-1.53	0.125	-.2201566	.0268149
population	.1712118	.1353135	1.27	0.206	-.0940054	.4364291
adequate	.0239296	.0227962	1.05	0.294	-.0207514	.0686106
objection	.0400114	.0352992	1.13	0.257	-.0291757	.1091985
_cons	12.48786	.3948532	31.63	0.000	11.71394	13.26178

Table 10. Loan size 0.5m $<$ X $\leq$ 1.5m

HDFE Linear regression
Absorbing 2 HDFE groups

Number of obs	= 26,227
F(8, 14844)	= 10.31
Prob > F	= 0.0000
R-squared	= 0.6849
Adj R-squared	= 0.4432
Within R-sq.	= 0.0093
Root MSE	= 0.6023

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.1241285	.0275546	4.50	0.000	.070118	.178139
real2loans	-.054576	.0189076	-2.89	0.004	-.0916372	-.0175149
drlnlsq	-.0034052	.0038288	-0.89	0.374	-.0109102	.0040997
roaq	.0789477	.0184889	4.27	0.000	.0427071	.1151882
hesecr	-.0159553	.0062044	-2.57	0.010	-.0281167	-.0037939
nonincr	-.1999678	.1153822	-1.73	0.083	-.4261312	.0261955
adequate	.1138655	.0509294	2.24	0.025	.0140375	.2136935
objection	.1263908	.0637916	1.98	0.048	.0013513	.2514303
_cons	11.96702	.3916616	30.55	0.000	11.19932	12.73473

Includes bank-county and year-county interaction effects

7.1.2. Bank county level (Purchased)

Table 11. Loan size $\leq$ 0.1m

```
HDFE Linear regression                            Number of obs   =    256,793
Absorbing 3 HDFE groups                           F(   9, 253041) =     878.83
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.3551
                                                  Adj R-squared   =     0.3455
                                                  Within R-sq.    =     0.0454
                                                  Root MSE        =     1.0897
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.8320566	.0136641	60.89	0.000	.8052754	.8588378
real2loans	.1474813	.0070866	20.81	0.000	.1335917	.1613709
drlnlsq	-.0163599	.0031438	-5.20	0.000	-.0225217	-.010198
roaq	-.0208868	.0100304	-2.08	0.037	-.0405462	-.0012274
hesecr	.0234953	.0008863	26.51	0.000	.0217581	.0252325
nonincr	-.7514089	.0428199	-17.55	0.000	-.8353347	-.6674831
population	-.320734	.5032824	-0.64	0.524	-1.307154	.6656861
adequate	-.3078397	.0246266	-12.50	0.000	-.3561072	-.2595721
objection	-.8401069	.0263791	-31.85	0.000	-.8918093	-.7884045
_cons	-1.478612	1.273505	-1.16	0.246	-3.974648	1.017425

Table 12. Loan size $\leq$ 0.1m

```
HDFE Linear regression                            Number of obs   =    189,386
Absorbing 2 HDFE groups                           F(   8, 119914) =     920.01
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.6128
                                                  Adj R-squared   =     0.3885
                                                  Within R-sq.    =     0.0840
                                                  Root MSE        =     1.0903
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	1.146635	.0180495	63.53	0.000	1.111258	1.182011
real2loans	.3312834	.0101165	32.75	0.000	.3114552	.3511115
drlnlsq	-.0318202	.0043071	-7.39	0.000	-.040262	-.0233784
roaq	.0749889	.013713	5.47	0.000	.0481115	.1018662
hesecr	.0269464	.0012075	22.32	0.000	.0245797	.0293132
nonincr	-.3809579	.0590157	-6.46	0.000	-.4966277	-.265288
adequate	-.3259386	.0341301	-9.55	0.000	-.3928331	-.2590441
objection	-.9244775	.0355455	-26.01	0.000	-.9941462	-.8548089
_cons	-7.873075	.3087716	-25.50	0.000	-8.478263	-7.267888

Includes bank-county and year-county interaction effects

Table 13. Loan size 0.1m $<$ X $\leq$ 0.25m

HDFE Linear regression	Number of obs	=	226,300
Absorbing 3 HDFE groups	F(9, 222659)	=	681.38
	Prob > F	=	0.0000
	R-squared	=	0.4161
	Adj R-squared	=	0.4065
	Within R-sq.	=	0.0301
	Root MSE	=	0.9028

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.515955	.0107326	48.07	0.000	.4949195	.5369906
real2loans	.106077	.0060867	17.43	0.000	.0941472	.1180068
drlnlsq	.009036	.0026537	3.41	0.001	.0038349	.0142372
roaq	.1646748	.0078869	20.88	0.000	.1492166	.1801329
hesecr	.0111723	.0009086	12.30	0.000	.0093915	.0129531
nonincr	-.9885321	.0427684	-23.11	0.000	-1.072357	-.9047071
population	1.041614	.227685	4.57	0.000	.5953576	1.487871
adequate	.1382703	.0158464	8.73	0.000	.1072117	.1693289
objection	-.2398938	.0171484	-13.99	0.000	-.2735042	-.2062834
_cons	1.150281	.6033026	1.91	0.057	-.032177	2.332739

Table 14. Loan size 0.1m $<$ X $\leq$ 0.25m

HDFE Linear regression	Number of obs	=	172,018
Absorbing 2 HDFE groups	F(8, 114176)	=	829.56
	Prob > F	=	0.0000
	R-squared	=	0.6176
	Adj R-squared	=	0.4238
	Within R-sq.	=	0.0716
	Root MSE	=	0.9259

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.8341681	.0156904	53.16	0.000	.8034151	.8649211
real2loans	.255745	.0096417	26.52	0.000	.2368474	.2746427
drlnlsq	-.0008126	.0038286	-0.21	0.832	-.0083166	.0066914
roaq	.22206	.0112321	19.77	0.000	.2000454	.2440747
hesecr	.0116336	.0012732	9.14	0.000	.0091382	.0141291
nonincr	-.9386353	.0610536	-15.37	0.000	-1.058299	-.8189712
adequate	.1147103	.0233371	4.92	0.000	.06897	.1604506
objection	-.4432693	.0247436	-17.91	0.000	-.4917665	-.3947721
_cons	-1.88782	.279149	-6.76	0.000	-2.434948	-1.340692

Includes bank-county and year-county interaction effects

Table 15. Loan size 0.25m $<$ X $\leq$ 0.5m

HDFE Linear regression	Number of obs	=	116,722
Absorbing 3 HDFE groups	F(9, 113982)	=	180.43
	Prob > F	=	0.0000
	R-squared	=	0.4351
	Adj R-squared	=	0.4215
	Within R-sq.	=	0.0173
	Root MSE	=	0.8771

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.2074973	.0124594	16.65	0.000	.183077	.2319176
real2loans	.1687629	.0104711	16.12	0.000	.1482398	.1892861
drlnlsq	-.0225038	.003242	-6.94	0.000	-.0288582	-.0161495
roaq	.1630166	.0108171	15.07	0.000	.1418153	.184218
hesecr	.0105233	.001312	8.02	0.000	.0079518	.0130948
nonincr	-.5617689	.0629126	-8.93	0.000	-.6850768	-.4384611
population	6.529013	.649027	10.06	0.000	5.25693	7.801096
adequate	.0937494	.0201523	4.65	0.000	.0542511	.1332477
objection	-.3010361	.0225316	-13.36	0.000	-.3451976	-.2568746
_cons	-6.401707	1.682997	-3.80	0.000	-9.700356	-3.103058

Table 16. Loan size 0.25m $<$ X $\leq$ 0.5m

HDFE Linear regression	Number of obs	=	85,478
Absorbing 2 HDFE groups	F(8, 57131)	=	306.03
	Prob > F	=	0.0000
	R-squared	=	0.6315
	Adj R-squared	=	0.4487
	Within R-sq.	=	0.0514
	Root MSE	=	0.9123

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.4244004	.0175179	24.23	0.000	.3900652	.4587355
real2loans	.4315862	.0126044	34.24	0.000	.4068816	.4562909
drlnlsq	-.0288598	.0048414	-5.96	0.000	-.0383489	-.0193706
roaq	.226501	.0156844	14.44	0.000	.1957596	.2572425
hesecr	.0121244	.0017656	6.87	0.000	.0086638	.015585
nonincr	-.7841234	.091386	-8.58	0.000	-.9632404	-.6050063
adequate	.0874663	.0329448	2.65	0.008	.0228944	.1520382
objection	-.4936621	.0350266	-14.09	0.000	-.5623144	-.4250098
_cons	6.907764	.3018043	22.89	0.000	6.316226	7.499303

Includes bank-county and year-county interaction effects

Table 17. Loan size 0.5m $<$ X $\leq$ 1.5m

```
HDFE Linear regression                            Number of obs   =     54,314
Absorbing 3 HDFE groups                           F(   9,  52522) =      63.76
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.4147
                                                  Adj R-squared   =     0.3947
                                                  Within R-sq.    =     0.0136
                                                  Root MSE        =     0.8613
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.1076499	.0165218	6.52	0.000	.075267	.1400327
real2loans	.104151	.0145227	7.17	0.000	.0756863	.1326158
drlnlsq	.0040771	.0038978	1.05	0.296	-.0035625	.0117168
roaq	.1367957	.0159774	8.56	0.000	.1054798	.1681116
hesecr	.0239755	.0020819	11.52	0.000	.0198949	.0280561
nonincr	.1687803	.096297	1.75	0.080	-.0199628	.3575234
population	6.985816	.9937132	7.03	0.000	5.038129	8.933503
adequate	-.0339572	.0297523	-1.14	0.254	-.092272	.0243575
objection	-.4220447	.0364083	-11.59	0.000	-.4934054	-.3506841
_cons	-5.668135	2.604489	-2.18	0.030	-10.77296	-.5633131

Table 18. Loan size 0.5m $<$ X $\leq$ 1.5m

```
HDFE Linear regression                            Number of obs   =     36,043
Absorbing 2 HDFE groups                           F(   8,  22299) =      86.29
                                                  Prob > F        =     0.0000
                                                  R-squared       =     0.6424
                                                  Adj R-squared   =     0.4220
                                                  Within R-sq.    =     0.0453
                                                  Root MSE        =     0.9195
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.2855676	.0258276	11.06	0.000	.2349436	.3361916
real2loans	.2875289	.0228877	12.56	0.000	.2426675	.3323903
drlnlsq	-.01375	.0064918	-2.12	0.034	-.0264744	-.0010256
roaq	.2492171	.0257921	9.66	0.000	.1986629	.2997714
hesecr	.0367371	.0030159	12.18	0.000	.0308258	.0426484
nonincr	-.061964	.152876	-0.41	0.685	-.3616116	.2376836
adequate	-.0674677	.0523784	-1.29	0.198	-.170133	.0351977
objection	-.7940006	.0639739	-12.41	0.000	-.9193939	-.6686073
_cons	10.01717	.4366995	22.94	0.000	9.161213	10.87314

Includes bank-county and year-county interaction effects

7.1.3. Bank state level (origjnated and purchased)

Table 19. Loan size $\leq$ 0.1m

```
HDFE Linear regression                            Number of obs   =    332,932
Absorbing 2 HDFE groups                           F(  59,   3128) =     210.96
Statistics robust to heteroskedasticity           Prob > F        =     0.0000
                                                  R-squared       =     0.2892
                                                  Adj R-squared   =     0.2787
                                                  Within R-sq.    =     0.2010
Number of clusters (fips)     =      3,129        Root MSE        =     1.0664

                                (Std. Err. adjusted for 3,129 clusters in fips)
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.636656	.0111436	57.13	0.000	.6148066	.6585055
real2loans	.2303326	.0067773	33.99	0.000	.2170443	.2436209
drlnlsq	-.009626	.0019952	-4.82	0.000	-.0135381	-.0057139
roaq	.019107	.0069192	2.76	0.006	.0055405	.0326736
hesecr	.0229694	.0008694	26.42	0.000	.0212648	.0246739
nonincr	-.7395904	.0364231	-20.31	0.000	-.8110059	-.6681749
population	4.800361	.1824918	26.30	0.000	4.442545	5.158177
adequate	-.4918439	.0180308	-27.28	0.000	-.5271973	-.4564904
objection	-1.006455	.0211387	-47.61	0.000	-1.047903	-.9650084

Table 20. Fixed effects states dummy coefficients (Loan size $\leq$ 0.1)

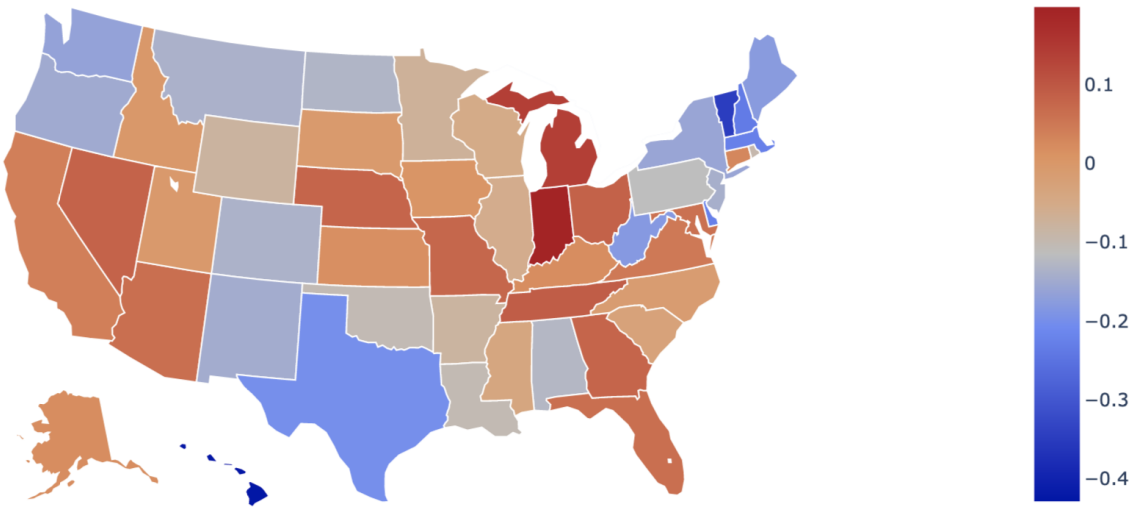

Table 21. Loan size 0.1m $<$ X $\leq$ 0.25m

HDFE Linear regression		Number of obs =	299,892
Absorbing 2 HDFE groups		F(59, 3062) =	197.23
Statistics robust to heteroskedasticity		Prob > F =	0.0000
		R-squared =	0.3341
		Adj R-squared =	0.3227
		Within R-sq. =	0.2629
Number of clusters (fips) =	3,063	Root MSE =	0.8974

(Std. Err. adjusted for 3,063 clusters in fips)

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.3914799	.010451	37.46	0.000	.3709882	.4119715
real2loans	.1414778	.0057093	24.78	0.000	.1302835	.1526722
drlnlsq	.0014382	.0016288	0.88	0.377	-.0017555	.0046319
roaq	.1369632	.0060456	22.65	0.000	.1251093	.1488171
hesecr	.0112901	.0008205	13.76	0.000	.0096813	.0128988
nonincr	-.8525077	.0383462	-22.23	0.000	-.9276947	-.7773207
population	5.008571	.1379918	36.30	0.000	4.738005	5.279137
adequate	.0323766	.0110864	2.92	0.004	.010639	.0541141
objection	-.313606	.0127799	-24.54	0.000	-.3386641	-.2885478

Table 22. Fixed effects states dummy coefficients (Loan size 0.1m $<$ X $\leq$ 0.25m)

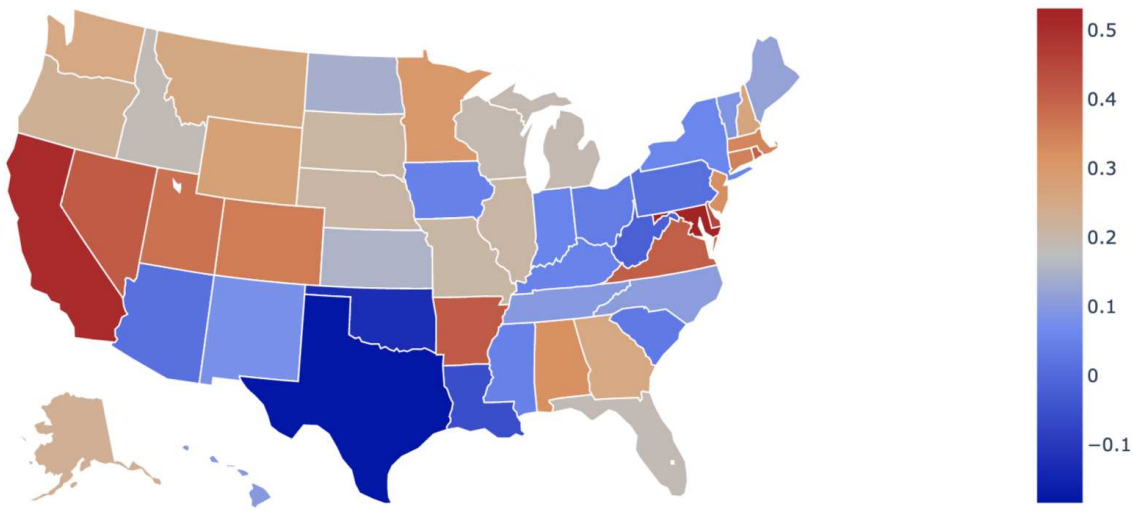

Table 23. Loan size 0.25m $<$ X $\leq$ 0.5m

HDFE Linear regression		Number of obs	= 162,451
Absorbing 2 HDFE groups		F(59, 2771)	= 162.44
Statistics robust to heteroskedasticity		Prob > F	= 0.0000
		R-squared	= 0.3454
		Adj R-squared	= 0.3276
		Within R-sq.	= 0.2516
Number of clusters (fips)	= 2,772	Root MSE	= 0.8632

(Std. Err. adjusted for 2,772 clusters in fips)

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.1663179	.0104835	15.86	0.000	.1457616	.1868742
real2loans	.198149	.0087936	22.53	0.000	.1809064	.2153917
drlnlsq	-.0120695	.0019292	-6.26	0.000	-.0158523	-.0082868
roaq	.1063589	.0086359	12.32	0.000	.0894254	.1232924
hesecr	.0098628	.0011748	8.40	0.000	.0075593	.0121664
nonincr	-.4524316	.0548403	-8.25	0.000	-.5599635	-.3448997
population	4.198454	.1545385	27.17	0.000	3.895432	4.501476
adequate	.0108977	.0143992	0.76	0.449	-.0173365	.0391319
objection	-.3262937	.0157912	-20.66	0.000	-.3572575	-.29533

Table 24. Fixed effects states dummy coefficients (Loan size 0.25m $<$ X $\leq$ 0.5))

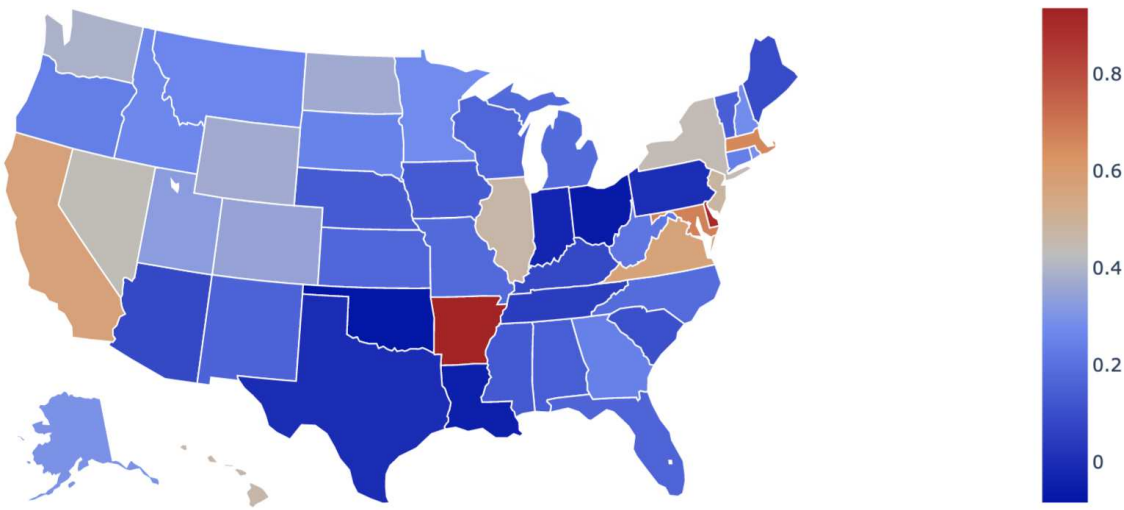

Table 25. Loan size 0.5m $< X \leq$ 1.5

```
HDFE Linear regression                            Number of obs   =     98,766
Absorbing 2 HDFE groups                           F(  59,    2536) =     51.66
Statistics robust to heteroskedasticity           Prob > F        =    0.0000
                                                  R-squared       =    0.2754
                                                  Adj R-squared   =    0.2454
                                                  Within R-sq.    =    0.1780
Number of clusters (fips)     =       2,537       Root MSE        =    0.8278

                                (Std. Err. adjusted for 2,537 clusters in fips)
```

lamt	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
asset	.0554988	.0112209	4.95	0.000	.0334957	.0775018
real2loans	.0509827	.0096053	5.31	0.000	.0321477	.0698178
drlnlsq	.001942	.0018427	1.05	0.292	-.0016714	.0055554
roaq	.0705797	.0095828	7.37	0.000	.0517888	.0893706
hesecr	.0156963	.0018485	8.49	0.000	.0120717	.019321
nonincr	.0727477	.0557453	1.31	0.192	-.0365633	.1820588
population	3.066041	.2212337	13.86	0.000	2.632224	3.499858
adequate	-.0495335	.0188793	-2.62	0.009	-.0865539	-.0125131
objection	-.2657206	.0278886	-9.53	0.000	-.3204073	-.2110339

Table 26. Fixed effects states dummy coefficients (Loan size 0.5m $< X \leq$ 1.5)